Analysis of Air Pollution Models in the context of Coupled Carbon and Air Pollution Benefits in Multi-scale Urban Systems

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Table of Contents

List of Figures

List of Tables

Chapter 1 - Introduction

Cities exist as centers of population, economic activity, and innovation, housing over 50% of the global world's populations and accounting for approximately 71% of global energy-related GHG emissions (UN-Habitat 2011). However, conventionally greenhouse gas mitigation strategies and their benefits have been analyzed at larger spatial scales (e.g. state, national). Currently, cities around the world are grappling with serious air quality challenges that require action from local and national policymakers to protect the well-being of urban residents. Many cities around the world have annual air pollution levels exceeding the WHO standards (Health Effects Institute, 2019) and globally this excess ambient air pollution contributed to 2.9 million premature mortalities in 2017 (Stanaway et al., 2018). It is well-known that air pollution (specifically PM2.5) has significant implications for health and well-being in cities worldwide and that the cities around the world could alleviate large environmental health burdens by reducing PM2.5 levels to those recommended by the World Health Organization (West et al. 2013, WHO 2018).

Further, when the benefits of GHG mitigation plans are analyzed, the focus generally on reducing climate-related damages in terms of agriculture productivity losses, heat stress, sea level rise etc. (Hsiang et al. 2017). Few analyses have taken into account the co-benefits of reduced air pollution arising from carbon mitigation strategies that reduce fossil fuel combustion. It is particularly challenging to align carbon and air pollution benefits because carbon emissions will have global impacts while air pollution emissions have local/regional impacts. Recently, the health co-benefits of reduced air pollution arising from climate action (e.g. NDCs, Paris Climate Agreement, etc.) have been recognized as potentially larger than the mitigation costs and avoided climate damages (Markandya et al. 2018; WHO 2018; Nemet et al. 2010). Unlike carbon emissions which are well-mixed in the atmosphere, the benefits of air pollution reductions are localized. Most air pollution-related mortality is concentrated in cities due to the higher population density and co-location of multiple emission sources. However, limited tools have been developed with the ability to compare and contrast urban climate mitigation policies in the context of air pollution co-benefits at the urban scale. Tools able to address multiple benefits at the urban scale must be spatially granular enough to differentiate between local and non-local emission sources. This is particularly challenging because the relevant emission sources and sectors may not be the same across cities, and because aligning the carbon and air pollution inventories may be challenging if they were developed using different data sources or across different spatial scales.

In general, co-benefits have become a widely-used but an ill-defined concept. In the climate literature carbon co-benefits refer to the ancillary benefits which are defined here based upon the associated reduction in criteria air pollution emissions. Although they have become popularized, the science behind quantifying these impacts has been mainly focused at the national level and there is limited coverage of the distribution of these benefits and how they vary at the city-level (Deng et al. 2018). Given the multiple spatial scales at which carbon mitigation is occurring, it is important to discuss the benefits of a low-carbon intervention across scale with particular attention to the institutions and actors implementing policy with co-benefit implications.

At the national scale: In the air pollution literature, co-benefits are framed as an essential component of cost-benefit analyses of pollution controls that create philosophical challenges in determining what the optimal level of pollution control is to maximize social welfare. For example, when the USEPA determines the value of reducing a unit of pollution through regulation, it must also evaluate the value of co-pollutants are reduced incidentally as a result of the policy in question. Recent debates in the Supreme Court over Mercury and Air Toxics Standards for power plants (Levinson 2018) illustrate how valuing the ancillary co-benefits of PM2.5 and CO2 reductions could increase the benefits of the standards by three orders of magnitude.

From a climate policy perspective, previous work evaluating the co-benefits assessed by integrated assessment models for optimizing climate policy found that the majority do not account for air quality co-benefits (Nemet et al. 2010); further these models do not optimize based on social welfare, but rather minimize costs of implementation due to the uncertainty in reduction of climate damages. Others (Wu et al. 2017; Thompson et al. 2014) have documented the ancillary air pollution co-benefits of carbon mitigation at regional and national scales and have advocated for including these benefits into any optimization or comparison of strategies addressing carbon mitigation (Hamilton et al. 2017; Markandya et al. 2018) because these health benefits may be greater than the climate benefits.

As Nemet (2010) and others have pointed out, most IAMs investigating the costs and benefits of carbon mitigation have left out the discussion of health co-benefits due to uncertain estimates of global or local benefits. The social cost of carbon provides a first order estimate of climate damages (USEPA) but was thought to be an underestimate at $36/ton (Harvey 2017, Stoerk et al. 2018). Due to the complex relationship between air pollution emissions and health endpoints (Henneman et al. 2017), there is a fair degree of uncertainty regarding the health benefits of each individual policy that has air pollution impacts. Globally, air pollution co-benefits related to PM2.5 and ozone damages in East Asia have already been shown to be 10-70 times higher than marginal carbon mitigation costs (West et al. 2013). Although uncertainty exists in both the health/carbon benefits estimations, other comparisons (Hamilton et al. 2017) on a per ton CO2 basis have shown that at the national scale health benefits are greater than carbon (for all but 2 countries). Further, these health benefits of PM2.5 reduction are more immediate than climate benefits; therefore we agree with others (Hamilton et al. 2017, Bollen et al. 2009, Nemet et al. 2010) that have advocated for including these benefits into any optimization or comparison of strategies addressing carbon mitigation; especially at the city scale where populations and air pollution are concentrated.

Population density and air pollution emissions are concentrated in cities, where the inclusion of air quality co-benefits in climate policy likely changes the optimal design of climate policy. More importantly, inclusion of these health co-benefits changes the distribution of those benefiting from climate policy with air quality co-benefits dependent on emissions location whereas avoided climate damages will be independent of emissions location. Although recent work (Li et al 2018, Thompson et al. 2014) has quantified health benefits of climate policy, these models are unable to specifically isolate urban co-benefits due to the need to highly localized emissions data and spatially-resolved air pollution and transport models. It's clear that any policy seeking to optimize health co-benefits of reductions in air pollution should take into account the differential distribution of the subnational benefits both domestically (Muller and Mendelsohn 2011) and globally (West et al 2013; Apte et al. 2015).

At the city-scale: Local policymakers may be interested in the tradeoffs of different environmental policy interventions., particularly as they relate to urban infrastructure interventions. These infrastructure systems (e.g. regional electricity transmission, regional transportation networks) may serve human activity in urban areas and could span multiple scales (e.g. city, state, region). As urban areas look to transition to an increasingly decarbonized, clean energy economy, there is a need for tools that are able to address the multiple ancillary benefits of infrastructure transition.

Addressing coupled carbon and air pollution benefits at the urban scale requires a discussion of the complexity of urban systems. Previous works, such as the Social-Ecological-Infrastructural Systems (SEIS) framework (Ramaswami et al. 2012), have illustrated the need to view urban systems across multiple scales and multiple sectors given the interconnectedness of infrastructure systems and the embeddedness of cities within larger scale infrastructure systems. This informs both the risk to natural resource supply chains serving the city and infrastructure interventions which could have multiple carbon, environment, and health benefits but require enhancing the capacity of policy actors and governance networks across multiple scales (Ramaswami et al. 2016). Given rapid urbanization in developing countries and aging infrastructure in developed countries, there is a need for smart infrastructure investments to ensure that the infrastructure transitions occurring across multiple sectors support the public good. The science for guiding these emerging social, technological, and infrastructural innovations occurring in urban areas is still in its infancy but needs to be further developed to ensure that these innovations advance multiple sustainability outcomes, locally and globally (Ramaswami et al. 2018).

As cities experiment with new technologies to improve functionality of infrastructure, new spatial planning models have been developed to examine the tradeoffs between the multiple benefits of infrastructure interventions, for example in the case of green infrastructure (Meerow and Newell 2017). Multiple frameworks have been suggested for developing decision support tools to allow policymakers to compare and contrast the impacts of urban infrastructure systems along multiple sustainability/environmental indicators (Sahely, Kennedy, and Adams 2005; Chrysoulakis et al. 2013; Carli, Dotoli, and Pellegrino 2018). Particularly as we think of low carbon actions in carbon-intensive infrastructure sectors which demand large amounts of energy such as transportation and buildings, there is a need for tools that can assess the energy, carbon, and air pollution implications of interventions that could either reduce demand or decarbonize energy supply. Assessing these multiple benefits at the city-scale requires sub-nationally differentiated carbon and PM2.5 emissions data including the location of pollution sources relative to population centers.

As cities begin to decarbonize and promote clean energy transitions, it is important to note that the health benefits of reducing air pollution may outweigh any subsidies or additional costs of transitioning from fossil fuels (Markandya et al. 2018; Coady et al. 2019). These health benefits will not be distributed equally however due to the localized nature of air pollution and transport mechanisms (Anderson et al. 2018; Cushing et al. 2018). Others have pointed out that co-benefits are large (Markandya et al. 2018) and concentrated in cities (West et al. 2013). We know these benefits will be distributed unevenly (Muller and Mendelsohn 2009) due to the localized nature of air pollution concentration and exposure and that historically air pollution has been concentrated in certain low income and minority communities (Cushing et al 2018; Clark, Millet and Marshall 2014). While many local governments have committed to reducing these inequities, It is not necessarily clear which policies or interventions reduce pollution in concentration hotspots compared to which policies reduce overall air pollution. For example, closing down a power plant located in a low-income minority neighborhood within the city core will impact air quality levels within the neighborhood and across the city due to dispersion of directly emitted PM2.5 and secondary formation of PM2.5 from precursors such as sulfates and nitrates

At the individual, consumer-scale: There is a need for tools that can evaluate the multiple benefits of products in consumer goods in support of ensuring sustainable consumption and production patterns (UN Sustainable Development Goal 12). Consumers looking to improve the sustainability of supply chains and reduce their environmental impact need tools that are able to differentiate and compare the multiple environmental objectives which may be of concern. For example, certification and rating systems, like GoodGuide (Guy 2016), provide consumers with a simplified rating system to evaluate products based upon multiple environmental health and sustainability metrics informed by life cycle assessment methods. For consumers to make decisions based upon the multiple environmental objectives that they may prioritize differently, they need tools that not only synthesize environmental metrics, but also allow them to evaluate tradeoffs. For example, as a consumer, how do you differentiate between products that may have carbon, resource efficiency (e.g. water), air pollution benefits?

Specifically addressing carbon and air pollution benefits at the individual/residential scale requires consumption-based carbon footprinting methods that can attribute pollution to the goods and services purchased by an individual consumer coupled with spatially-specific carbon and air pollution emission inventory for air pollution modeling (Tessum et al. 2019). The spatial inventory is critical due to the variation in environmental impacts (Smith et al. 2017; Tessum, Hill, and Marshall 2014) depending on where resource extraction takes place and the variation in marginal benefits depending on where air pollutants are emitted. For example, when buying a new vehicle, the carbon benefits of increased fuel efficiency in vehicles may be rated on a different metric (e.g. miles per gallon) than the local air pollution benefits of reduced tailpipe emissions (e.g. smog rating). Further, if the consumer is choosing between vehicle fuel alternatives to petroleum there will be a tradeoff between electric vehicles (which could reduce local carbon and air pollution emissions) and biofuel-based vehicles (which may reduce carbon but lack air pollution reductions and exacerbate agriculture/land-use concerns)

Therefore, any discussion of carbon and air pollution benefits will be nuanced depending on the scale at which the intervention is taking place. Air quality is likely best managed at the state-regional level in order to control both cross-state pollution and the transfer of pollution between urban-rural areas. Further, because PM2.5 levels in urban areas are dependent on primary PM2.5 formation (<50km) and secondary PM2.5 formation (>50 km), it is necessary to estimate the influence of local and non-local pollution sources. Given the diverse set of pollution sources that could contribute to local air quality challenges at the urban-scale, it is important to consider both urban sources of pollution that can affected by city government and local actors and non-urban sources of pollution that could be influenced by infrastructure sectors (e.g. electricity) outside of the city. Current air pollution and carbon tools are well-suited for state-regional pollution management but lack the spatial granularity necessary to address these issues at the city-scale. Particularly because cities and urban planners are taking action to transition to more sustainable infrastructure systems, there is a need for tools that can assess the multiple benefits (carbon, air pollution, etc.) that could occur as a result of these new infrastructure systems. Secondly, because there is a growing desire among state and local policymakers to make sure that any interventions to reduce carbon/air pollution also improve the distribution of pollution burdens, there is a need for spatially-resolved tools that can measure the intracity variability of air pollution exposure and the potential for these interventions to reduce pollution hotspots.

Beyond the challenges of obtaining emissions data with the spatial granularity necessary to evaluate urban co-benefits, air pollution modeling itself is very complex. The urban air pollution co-benefits modeling is particularly complex due to three phenomena, 1) transboundary carbon emissions from urban use-activity, 2) transboundary air pollution emission transport across cities, their hinterlands, and neighboring urban areas, and 3) the variation in intraurban air pollution concentrations at fine-scales (e.g. census block, census tracts), which is important for discussions around equity, both impact the spatial distribution of health impacts in cities.

In order to address co-benefits in urban systems, these challenges require state-of-the-art scientific tools that can attribute changes in air quality to specific sources of pollution and can differentiate between pollution exposure changes within cities. The following dissertation explores these issues to determine how the state-of-the-science tools can be used to inform carbon mitigation actions which have air pollution and health co-benefits. Together, these chapters seek to inform the discussion surrounding the distribution of air pollution and carbon co-benefits in order to design more optimal environmental policies moving forward. The focus of this dissertation is on developing methods for the spatial analysis of air pollution co-benefits across multi-scale urban systems to support their evaluation in the context of carbon mitigation actions. The remained of the dissertation is organized across the following chapters:

Ch. 2 - Review of Fine-Scale Air Quality Modeling for Carbon and Health Co-Benefits Assessments in Cities - The second chapter explores available air quality models that can be applied to coupled carbon and air pollution benefits analysis in cities and the criteria necessary to evaluate model application.

Ch. 3 - Methodology to Prioritize Urban infrastructure interventions considering carbon, air *pollution emissions and cost minimization* - The third chapter applies one of these tools in Chinese cities to explore the variability in intercity air pollution benefits and how urban only pollution control strategies can be optimized to maximize health benefits.

Ch. 4 - Fine-Scale Air Quality Models for Assessing Social Justice in the context of Local Carbon Mitigation Actions - The fourth chapter compares conventional air pollution dispersion models with a new reduced complexity tool (InMap) to determine what policy questions can be informed by the state-of-the-science using Minneapolis as a case study.

Ch. 5 - Bounding the co-benefits of carbon reductions in California: Aggregate and distributional impacts - The last chapter focuses on the debate in California about carbon co-benefits in disadvantaged communities to determine if the current suite of climate policies being implemented alleviates pollution burdens in front-line communities or if environmental justice groups concerns about market-based environmental policies are appropriate.

Chapter 2 - Review of Fine-Scale Air Quality Modeling for Carbon and Health Co-Benefits Assessments in Cities

Synopsis

Global cities are simultaneously taking action to improve air quality and mitigate climate change by reducing emissions from energy and infrastructure systems. Cities are uniquely positioned to achieve improved environmental policy by managing carbon, air pollution, and health co-benefits concurrently due to the concentration of people and economic activity in cities. By accounting for the air pollution co-benefits of carbon mitigation, cities may create more political support for reducing emissions and energy use due to the large health benefits of reducing local air pollution exposure. Given the policy-relevant implications of co-benefits at the city-scale, this review evaluates the existing tools/models to assess both carbon and air pollution in urban environments.

1. Introduction

Globally, cities exist as centers of population, economic activity, and innovation. Currently, cities around the world are grappling with serious air quality challenges that require action from local and national policymakers to protect the well-being of urban residents. Many cities around the world have annual air pollution levels exceeding the WHO standards (Health Effects Institute, 2019) and globally this excess ambient air pollution contributed to 2.9 million premature mortalities in 2017 (Stanaway et al., 2018). As policymakers attempt to reduce urban air pollution exposure, they are challenged by air pollution emission sources which exist outside the city (and which they may not be able to manage) and inequities in intracity air pollution levels due to pollution “hotspots”.

Cities are also important centers of climate change action as evidenced by the over 9,000 cities that have committed to the Global Covenant of Mayors for Climate and Energy and various organizations (e.g., ICLEI, C40, etc.) which support cities in their efforts to mitigate and adapt to climate change. Because cities are embedded within larger infrastructure and trade networks, various tools have been developed to assess current community-wide emissions, project future greenhouse gas (GHG) emissions, and assess the impact of climate mitigation policies.

Because cities are concurrently trying to manage carbon and air pollution emissions, urban environmental policies should take into account the co-benefits of carbon mitigation, particularly as they relate to reducing local air pollution levels. Recent literature (Mayrhofer and Gupta, 2016; Nemet, Holloway, and Meier, 2010) has documented the challenges of quantifying co-benefits, but the health benefits of reducing air pollution are too large to ignore. The health benefits of the reduction in air pollutants (PM2.5) from both clean energy and carbon mitigation policies may outweigh the costs of carbon mitigation in the United States (Fowlie, 2018) and globally (Markandya et al., 2018). Further, we know these benefits will be heterogeneous (Muller and Mendelsohn, 2009; Goodkind et al., 2019) and we know they will be concentrated in cities (West et al., 2013). The heterogeneity and size of these health benefits means that they also have significant equity implications (Anderson et al., 2018; Cushing et al., 2018). It is therefore important to develop accurate estimates of these benefits at the urban scale, so that the size and distribution of health co-benefits of carbon mitigation are accurately reflected in environmental policies.

For cities grappling with air quality challenges, the first question is how can we reduce annual average air pollution levels and the number of acute pollution episodes? The answer to this question varies from city-to-city depending on the economic structure of the city and various physical and meteorological characteristics. In particular, cities must identify which sectors (industrial, transportation, residential, agriculture, etc.) contribute to their local air quality challenges and whether the sources of pollution are located within or outside the city. Once policies are identified that will prove beneficial to reducing exposure to local air pollution, the next question becomes how do we make sure these benefits are distributed fairly? Potential approaches to distributing these health benefits equitably are complicated by economic (e.g., Where are marginal benefits highest? Where are marginal costs lowest?) and political concerns (e.g., Which neighborhoods historically have high levels of pollution? Does a given policy reduce this burden?). Policymakers seek to address both sets of questions as they develop strategies for urban air quality management, therefore, co-benefit models need to account for emissions inside and outside the city, while assessing changes in air quality within the city.

Separately, cities have also been developing carbon emission inventories for local climate action planning and for reporting to the Global Covenant of Mayors in Climate and Energy. Carbon accounting of community-wide emissions for cities has become more standardized over the past few years as cities have begun to report emissions through the Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (GPC) (Fong et al., 2014). Community-wide carbon emissions are reported across multiple spatial scales grouped by three categories:
Scope 1 emissions: emissions that physically occur within the city
Scope 2 emissions: energy-related emissions from the use of electricity, steam, and/or heating/cooling supplied by grids which may or may not cross city boundaries
Scope 3 emissions: emissions that physically occur outside the city but are driven by activities taking place within the city's boundaries.

Historically, cities have used production-based approaches to quantify Scope 1 and 2 emissions. Production-based approaches have historically been ill-defined but many have used the term in reference to territorial emissions or emissions that are occurring geographically within the city boundary (Chen et al., 2019). Recent studies (Lin et al., 2015) have re-defined the term to account for the goods and services imported into the city that are used by industries/manufacturers to better account for the impact of industrial symbiosis and other interventions improving the efficiency of urban-industrial supply chains. But cities may account for different Scope 3 emissions depending on the methodology they are following. For example, many cities have used a consumption-based approaches (C40, 2018; Lin et al., 2017) which account for Scope 1, 2, and 3 emissions due to the production of goods and services that are consumed by residents of the city, but exclude emissions from exported goods and services that are produced by the city and consumed elsewhere. The production-based approach likely underestimates emissions in cities with high consumption activity (such as cities with tourist-based economies), while the consumption-based approach has limited application in cities with high industrial or manufacturing activity (Chavez and Ramaswami 2013). None of these approaches is perfect, but all seek to better account for carbon emissions associated with city activity that are outside the geographic boundary and it is therefore critical that there is transparency in the methods used to quantify these emissions. For cities using consumption-based approaches, there may be a spatial mismatch between the emissions accounted for in the carbon emissions inventory and the local/regional emissions required for air pollution modeling.

Many models and methods have been developed to manage urban air pollution and carbon emissions but few models have been able to address the nexus of carbon, air pollution, and health co-benefits within cities. Assessing co-benefits at the city-scale requires sophisticated models that are able to account for the transboundary nature of the supply chains supporting city activity and the potential for non-local emissions to impact local air quality, while also having the spatial resolution to accurately assess intracity air pollution concentrations. This review assesses the state-of-the-science tools that have been developed to assess co-benefits at the city-scale.

2. Overview of City-relevant Co-Benefit Models

Models which are able to assess carbon, air pollution, and health co-benefits are summarized below with a focus on nested models. This list is not meant to be exhaustive but illustrates how carbon and air pollution modeling methods can be coupled. Table 1 demonstrates how the authors' view the scope and spatial scale of models that have the ability to assess co-benefits of carbon and air pollution emission reductions. The first type of models develop carbon and air pollution co-pollutant inventories but assign air pollution/health benefits directly to each unit of emission without using air pollution and transport modeling to assess changes in air pollution concentration and exposure (e.g. UrbanFootprint (UrbanFootprint, 2013)). A second type of model (e.g., AERMOD) utilizes similar community-scale emission inventories to mechanistically estimate how changes in local emissions impact local air pollution concentration and exposure levels based upon non-linear dynamics of air pollution transport.

A third type of model, nested models, are most applicable to addressing city-scale co-benefits because they acknowledge the fact that city activity induces emissions outside the territorial boundary of the city. While the location of carbon emissions is not as important due to its global impacts, the location of air pollution emissions is critical to determining to associated impacts on air quality and pollution exposure. For example, SIM-Air (Guttikunda, Nishadh, and Jawahar, 2019; Guttikunda and Jawahar, 2012), GAINS (Wagner et al., 2018), COBRA (USEPA, 2018), and AP3 (National Research Council, 2010) are well-known models which utilize gridded emission inventories and regional estimates of air pollution transport and formation to predict changes in air quality/pollution exposure resulting from changes in emissions. Models like the Carbon Footprinting and Air Pollution Dispersion (CFAD) (Ramaswami et al., 2017) utilize community-wide carbon and air pollution inventories coupled with air pollution models (e.g., AERMOD) to distinguish between how changes in local and regional emissions may impact urban air quality and exposure. Lastly, Nested-Reduced Form models, like InMap (Tessum et al., 2019; Hill et al., 2019), have the potential to couple carbon and air pollution inventories at multiple scales (national, state, city) with reduced form air pollution models in order to estimate changing air quality and exposure at multiple scales resulting from changes in consumption of goods and services.

Table 2-1 Boundary of Carbon Emission Accounting and Air Pollution Exposure Models for City-Relevant Co-Benefit Models

Co-Benefit Models with the ability to couple across spatial scales are organized based upon the geographic boundaries of the carbon emission accounting and air pollution exposure.

		Boundary of Carbon Emission Accounting		
		Geographic (community-wide, Scope 1+2)	Geographic (community-wide, Scope 1+2+3)	Consumption-based (Scope 1+2+3)
Boundary of Air Pollution Modeling	Air Pollution Emission Inventories	UrbanFootprint		
	Community-scale Air Quality Models	AERMOD		
	Nested local-regional-national Models (Source-Receptor)	GAINS, SIM-Air, COBRA, AP3		
	Nested local-regional-national Models (Dispersion)		CFAD	
	Nested local-regional-national Models (Reduced Form)			InMap

3. Air Pollution Models

In order to assess carbon and air pollution co-benefits, air pollution models are required to connect spatially-explicit carbon and air pollutant inventories with air pollution formation and transport in the atmosphere. This is critical because of the non-linear relationship between air pollution emissions and air pollution concentrations (e.g., each unit of air pollutant emission may have a varied effect on concentration). Air pollution concentrations then become the unit of analysis for air quality standards, public health, and exposure estimates. The relationship between emissions and concentration may be governed by physical characteristics of the pollution source (e.g., stack height, toxicity of pollutants, etc.), non-linear dynamics of physical processes governing pollution in the atmosphere (e.g., transport, reaction, deposition, etc.), and geographic characteristics of the exposure site (e.g., topography, wind patterns, etc.). To accurately assess the impact of these factors, air pollution models are needed to determine the dynamics of each unit of emissions once they enter the atmosphere. For city-level co-benefits modeling, these tools need to have the potential utilize urban and regional emissions inventories while evaluating air pollution concentration at a fine-grained spatial resolution so that intercity and intracity air pollution/health benefits can be estimated. This means that the air pollution models that are most applicable at the city-scale need to balance data availability and accessibility with the computational complexity necessary to model air pollution transport and formation.

Given the uncertainty in modeling and the need to estimate air quality across varying spatial and temporal resolution, various methods exist for estimating air quality. Monitors are generally used to track air quality over time and to ensure compliance with air quality regulations; they also provide data validation for modeling results. Land use regression techniques use the historical data from monitors in comparison to land use variables (e.g., density) to predict air pollution levels with high spatial resolution. Recently, Aerosol Optical Dispersion techniques (Di et al., 2017; van Donkelaar et al., 2016) have advanced considerably, using satellite data with increasingly high spatial resolution to estimate air pollution concentrations over time in locations lacking monitoring data

While these methods are extremely sophisticated, they do not connect emissions reductions directly to concentration reductions. Therefore, these techniques are not able to directly inform policy design and implementation but are useful for empirical and historical air quality studies, for example, many studies have explored how health outcomes change before and after a policy change (e.g., Ebenstein et al., 2017). The models described below estimate air pollution concentrations and changes in exposure based on spatially-resolved emissions inventories. This is critical to developing prospective scenarios that determine a priori the benefits of policies and interventions which reduce air pollution.

The challenge for air pollution models is to balance the complexity of modeling atmospheric processes that induce primary and secondary formation of pollutants with the spatial and temporal resolution necessary to answer policy relevant questions, for example, where are high air pollution concentrations located or how can cities improve region-wide air quality? Urban air pollution concentration will be a function of the emissions (local and non-local) and the meteorological conditions (wind speed, wind direction, mixing height, etc.) that govern pollution formation at any given time. In practice, modelers must make the choice between model processing time and spatial resolution (Gilmore et al., 2019; Tessum, Hill, and Marshall, 2017). This tradeoff is very important for determining which models can assess the benefits of policy-induced emissions reduction at the city-scale.

3.1 Application of Fine-Scale Air Pollution Models to Co-Benefits in Cities

Air pollution models are tailored to specific spatial and temporal scales, which means they can estimate exposure across multiple scales ranging from global to between buildings. Figure 1-1 illustrates the spatial dimensions of carbon and air pollution emission inventories compared to the scale at which air pollution models operate. The discussion below will focus on those tools that have potential to be applied to urban-scale co-benefits evaluation and policy scenarios.

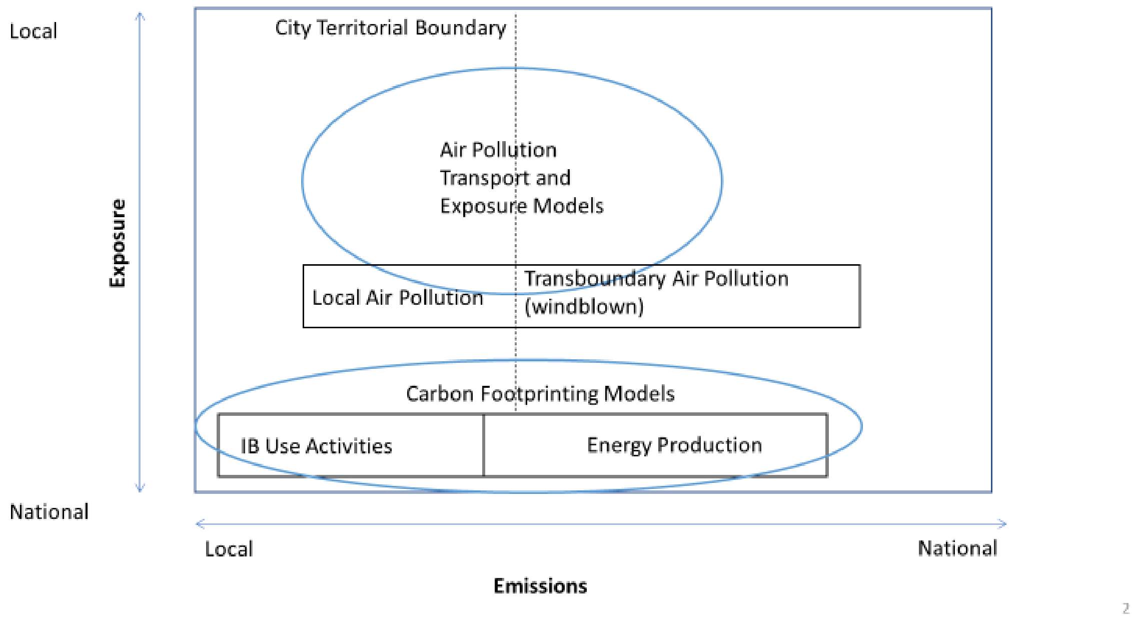


Figure 2-1 Spatial Dimensions of Carbon Footprinting and Air Pollution Models

Geographic Scale of Carbon/Air Pollution Models shown as blue circles and geographic scale of emissions inventories shown as black boxes. Although carbon and air pollution emissions are aligned at the city-scale, carbon and air pollution models evaluate outcomes at different scales because air pollution damages occur on a local-regional scale while climate damages occur on a global scale.

Models that are able to address co-benefits at the urban scale need to be designed to utilize emissions data that distinguishes between local and non-local emissions, estimate changes in air pollution exposure within cities, and be customizable to policies that are specific to the jurisdiction in question. Not all air pollution models will be well-suited to evaluate co-benefits at the city-wide scale, because many may be designed for alternate purposes such as regulatory compliance. The air pollution models which are most relevant need to differentiate between in-boundary and transboundary emissions so that urban and non-urban pollution control strategies can be evaluated. They must also account for the variation of inter- and intra-city air pollution exposure, so that the distribution of air pollution and health benefits can be assessed to determine which areas and populations will benefit most from air pollution control policies being considered. To systematically evaluate the air pollution and transport models that have the ability to estimate city-scale co-benefits, the following air pollution model characteristics need to be considered:

1. Primary/Secondary PM2.5 formation - Primary PM2.5 drives the local emissions component of urban PM2.5 concentrations because it consists of the particles directly emitted during the combustion of fossil fuels. In contrast, secondary PM2.5 is formed in the atmosphere by reactions between SOx, NOx, NH_3, etc. that may occur over larger provincial and regional areas

2. Spatial Resolution – Model inputs (emission inventories) and outputs (concentration estimates) will be set to a standardized or variable grid ranging from 0.1–50 km. The spatial resolution of these grids has implications for data availability and the model's ability to assess air pollution exposure within the city

3. Ground-Truthing and Relevance – Some models are comparable to real-time monitored air pollution levels, while others are intended to predict changes in air pollution levels based on changes in emissions. Recently, a number of reduced form tools (AP3, EASIUR, InMap) have been developed to quantify marginal benefits in pollution reduction. Critically, these reduced form tools do not claim to be more accurate than previous models, nor is their intention to be used for regulatory compliance. Instead, they focus on developing assessments of changes in pollution exposure due to policies that reduce local, regional, or national emissions.

4. Application – Certain air pollution models may be better suited for different policy-relevant questions. Models may be tailored to assess the health impacts of changes in emissions and exposure to air pollution, while others may be better suited for identification of concentrated areas of pollution.

Although a variety of air pollution models exist, the following section is focused on the subset of models that can be readily applied to city-scale co-benefits. It is critical to note that the most state-of-the-art models may not be widely-used by local policymakers due to data, computational, and technical capacity limitations. Reduced Form models have been developed to make air pollution models more accessible and more policy-relevant by reducing computational effort and allowing for broader evaluation tailored to location-specific policies/interventions. The following three sections evaluate three types of air pollution models using the criteria above to determine which air pollution and transport models are best-suited for different questions surrounding co-benefits at the urban-scale.

3.1.1 Dispersion Models

- *Description:* Gaussian plume dispersion models (e.g. AERMOD) estimate air pollution levels that are downwind of individual sources or source groups. They are useful for predicting pollution impacts within cities due to nearby sources but are not recommended for predictions of long range pollution transport (> 50km) (Cimorelli et al., 2005; USEPA, 2015)
- *PM2.5 Formation:* Primary PM2.5 only; assumes that increased concentration in cities is mainly due to local sources
- *Spatial Resolution:* Fine-Scale resolution (<1km) enables assessment of intracity air pollution exposure
- *Application:* Used for regulatory purposes to determine near-source impacts of large emitters, but generally cannot estimate secondary formation of PM2.5 or predict long-range pollution transport
- *Co-Benefits Examples:* Applied at the local to regional scale, can be nested with carbon footprinting models (e.g., CFAD) (Ramaswami et al., 2017)

3.1.2 Chemical Transport Models

- *Description:* Chemical Transport Models (CTMs) are three-dimensional mechanistic models that predict ambient concentrations of pollutants using mass balance principles accounting for emissions, transport, dispersion by winds, chemical transformations, and atmospheric removal processes. CTMs are the most scientifically sophisticated and rigorous tools available for linking emissions to ambient concentrations (e.g., CMAQ, WRF-Chem) (Byun and Ching, 1999; Grell et al., 2005)
- *PM2.5 Formation:* Primary and Secondary PM2.5 including gridded emission inventory of all PM2.5 precursors
- *Spatial Resolution:* Coarse (>4km) due to model complexity, computational processing time, and availability of nationwide fine-scale emissions inventory data (US-based models utilize the triennial National Emissions Inventory)
- *Application:* Can be compared to real-time air pollution monitoring and used for regulatory impact assessment, but limited spatial and temporal resolution
- *Co-Benefits Examples:* Applied at the National or Regional Scale (Thompson et al., 2016; Zhang et al., 2016)

3.1.3 Reduced Form Models

- *Description:* To improve the availability and accessibility of state-of-the-science CTM air quality modeling and cost estimates, the air quality research community has recently created a new set of simplified models, known as reduced form or reduced-complexity models, to estimate the marginal social costs of air pollution in terms of monetized health damages per pollutant (Gilmore et al., 2019). These models estimate marginal social costs with nested local-regional-national emission inventories.

- *PM2.5 Formation:* Variable - AP3 (Primary PM2.5 only), InMap (Primary and Secondary PM2.5 Formation)
- *Spatial Resolution:* InMap (1-48km) but coarser than dispersion models
- *Application:* Able to model prospective policy scenarios and sensitivity to model/scenario uncertainties due to lower computational intensity. These models are meant to estimate marginal air quality and health benefits based upon the changes in air quality that can be attributed to changes in emissions; may be limited in their comparability to real-time pollution data.
- *Co-Benefits Examples:* Applied at multiple scales - National (Markandya et al., 2018), Regional (Muller and Mendelsohn 2009), Local (Goodkind et al., 2019; Paolella et al., 2018)

Table 2-2 Summary of Air Pollution Models for Urban Application

In order of increasing computational complexity, this table provides examples, contribution, and limitations of air pollution models that can be applied to urban co-benefits

Increasing Complexity →

	Reduced Form Models	Air Pollution Dispersion	Chemical Transport Models
Example	InMap, AP3	AERMOD	CMAQ, WRF-Chem
Contribution	Less computationally intensive, predictions of marginal damages	High Spatial Resolution, intracity variability (identification of pollution hotspots)	State-of-the-art physical and chemical transport process model, most complete spatial/temporal coverage
Limitations	Limited temporal coverage, limited comparability to observed concentrations	Only primary PM2.5, not recommended for long-range transport	Computationally intensive, coarse spatial scale

In the US context, air pollution dispersion and chemical transport models have been used by state and national regulators to ensure regulatory compliance and perform regulatory impact assessments. These models on their own have robust applications to urban air quality management strategies, but are not necessarily aligned with local analyses that see to address carbon, air pollution, and health co-benefits. Dispersion and Reduced Form models have already been integrated with city-scale carbon accounting methods due to their ability to incorporate nested emission inventories at multiple spatial scales. Local policymakers and practitioners should use these tools or tools with similar functionality to quantify the magnitude and distribution of carbon, air pollution and health co-benefits

4. Conclusion

Reducing air pollution has significant benefits both globally and locally. Environmental policies that are designed and implemented at the local-regional scale must take into account both the magnitude and distribution of these health benefits because of their implications on cost-benefit analyses and developing political support for local environmental policies. Models developed to date have been limited in their ability to measure urban carbon and air pollution co-benefits. First, it has been challenging to acquire data on activity and emissions delineated between local sources and regional/national sources of pollution (>50km from city). Second, the complexity of state-of-the-art models leads to limitations in terms of the software/equipment, computational time, and technical capacity needed to apply these tools towards the development of local air pollution and carbon policy. Further, these state-of-the-art models have been designed for state/national level assessments and may not have the spatial resolution necessary to estimate local air pollution/health benefits.

A variety of commercially-available models have been developed to assess how carbon emissions will respond to changes in land-use, technology, and policy/behavior changes at the urban scale. Certain models also attempt to measure air pollution benefits of these changes using linear marginal benefits estimates (UrbanFootprint, 2013) or neural networks to predict air quality changes based on weather, traffic and air pollution sensor data (Siemens, 2019). While these estimates may have some predictive value, these models have limited ability to inform the design and implementation of local policies that impact air pollution. Models that inform policy should estimate both the change in criteria air pollutant emissions and the changes in local air pollution concentrations due to the non-linear relationship between air pollution emissions reduction and air pollution exposure reduction. This is critical because of the heterogeneity that exists in the marginal benefits of reducing one unit of air pollution and because these benefits will be higher within cities but distributed unequally throughout the city. These marginal benefits need to be estimated at high spatial resolution (e.g., sub-county scale) because there may be an order of magnitude difference within counties (Goodkind et al., 2019).

The recent development of reduced complexity models are a promising alternative, recognizing the importance of estimating the marginal benefits of reductions in air pollution with high spatial resolution and limited computational complexity (Gilmore et al., 2019). These models combine the ability to estimate the impact of both local/long-range pollution sources on air quality levels within cities with the granularity to estimate variations in air pollution exposure at the sub-county level. As these models develop and become used in discussions around equity (Tessum et al., 2019; Tessum, Hill, and Marshall, 2017), it is important to assess the relationship between mechanistic and empirical models.

The spatial resolution of relevant co-benefits models is a critical variable to assess, particularly when considering equity implications of the distribution of air pollution/health benefits (Paolella et al., 2018). Because carbon and air pollution emission inventories also take place across nested spatial scales (city, region, national), models addressing co-benefits must also have the ability to differentiate between urban and non-urban emission reductions. Models which can couple spatially-explicit emission inventories with regional air pollution transport methods are best suited for assessing co-benefits at the city-scale. If these models can combine regional air pollution transport with high spatial resolution at the sub-county scale, then they have the ability to inform environmental policy design so that the health benefits of reducing air pollution are both optimal and distributed more equitably.

Given the uncertainties in underlying local emissions, exposure, and demographic data, policymakers must acknowledge two key truths. First, not all emissions reductions are created equal; improving air quality across urban areas requires an understanding of the implications of emitter location and physical characteristics of local and non-local emitters. Second, the marginal health benefits of reducing local air pollution will not be distributed uniformly across the city, so policy needs to be designed to account for the presence of concentrated areas of pollution, particularly when addressing multi-pollutant policies (e.g., policies and interventions which reduce multiple pollutants, such as carbon and criteria air pollutant emissions). The complex nature of air pollution and atmospheric transport has resulted in multiple models that may be able to serve different co-benefits related questions. Moving forward, it is critical that the modeling community develop tools that are suited to the questions that policymakers are asking so that environmental policy design is being informed by the best available science. These tools need to have the ability to utilize emissions data across multiple spatial scales spanning local city boundary while also measuring air pollution exposure at the intracity scale. The existing suite of tools are not perfect but can be used to evaluate the magnitude and distribution of carbon, air pollution, and health co-benefits in cities. Policymakers can use these tools for prospective analyses to determine which carbon and air pollution policy options may have the most health benefits at the city-scale and then utilize other empirical methods involving satellite-derived and monitor air quality data to verify these policies are improving air quality and health outcomes.

Chapter 3 - Methodology to Prioritize Urban infrastructure interventions considering carbon, air pollution emissions and cost minimization

1. Introduction

Globally, cities house more than 50% of the world's population and contribute 70% CO2 emissions, while ambient air pollution worldwide led to >4 million premature mortalities globally in 2014. Others have noted elsewhere that the human health impacts likely outweigh the near-term climate impacts (Shindell et al. 2012) and these health impacts are likely to be concentrated in cities (West et al. 2013; Pascal et al. 2013). The high concentration of people and megacities in Asia means much of the health impacts of ambient air pollution are likely to be distributed there (Apte et al. 2015). The majority of health benefits from air pollution reduction are dominated by the reduction in health impacts attributable to particulate matter below 2.5 microns ($PM_{2.5}$) (US EPA 2011). Globally, many cities still struggle to meet WHO air quality standards in both developed and developing countries. The highly publicized air pollution issues and the industrial development in Chinese cities may mirror the challenges future urban centers will face in a carbon constrained world.

Chinese cities' challenges to achieving air quality targets, such as $PM_{2.5}$ concentrations below the 10 μg/m3 WHO standard and the 35 μg/m3 national standard, have been well-documented in the media and in literature (Fu et al. 2016). China's rapid urbanization coupled with co-located rapid industrialization has created a hazardous ambient environment for urban dwellers, leading to the prominence of air pollution control in the national government's policy agenda (Jin et al. 2016). In addition to the air quality control policies, China has also committed to carbon mitigation targets which will require reductions in urban and industrial energy use, as these two sectors account for 60% and 62%, respectively, of China's national CO2 emissions (Ohshita et al. 2015).

Therefore, cities present a potential action arena for both reducing local air quality and health hazards and reducing global climate pollutants (carbon) through reductions in local emissions.

Cities may invest in new urban energy infrastructure in order to increase capacity of infrastructure services to meet increasing demand, adhere to national policy mandates, or to integrate emerging technologies. Infrastructure investments in industrial, buildings, transportation, and heating efficiency could have benefits in reducing energy use, costs, carbon, and air pollution emissions. Given these multiple benefits, cities need tools that can inform the prioritization of different infrastructure interventions across multiple objectives, such as reducing cost, carbon emissions, and air pollution emissions. Particularly, as cities invest in circular economy strategies such as material and heat exchange across industrial, residential and commercial sectors, it is necessary to have methods for maximizing and comparing the multiple benefits that these strategies may provide.

While there are multiple tools that can address co-benefits [e.g. GAINS], there are few tools for analyzing coupled carbon and air pollution prioritization of interventions at the urban scale (Deng et al. 2018). One reason for this is the difficulty with aligning urban carbon emission inventories (which generally account for Scope 1 and 2 emissions) with air pollution inventories which need to delineate between urban and non-urban emission sources. For example, cities may invest in strategies to reduce electricity use, but may not know where/which power plant is reducing emissions as a result. A second reason is that improving urban air quality is a function of both emissions within the city and transboundary emissions (e.g. windblown air pollution transported into the city). This means that to evaluate air quality co-benefits, cities need to not only know where emissions are being reduced, but also require sophisticated air pollution/transport models that can estimate how local/non-local emission reductions impact urban air quality.

Conventionally, policymakers turn to end-of-pipe strategies (e.g. installing control equipment on smokestacks) to reduce criteria air pollutant emissions and improve air quality. While these strategies have been proven useful for reducing air pollution, there are usually no benefits in terms of carbon or energy intensity reduction (and there may even be carbon emission increase if there are energy penalties for installing control equipment) . Circular economy and urban energy efficiency strategies may also reduce air pollutant emissions but will also reduce carbon and energy intensity. Critically, in order to compare these two types of pollution reduction strategies, policymakers need tools that can evaluate coupled carbon and air quality benefits.

China provides an interesting context for co-benefits given their Paris commitment to nationally determined contributions (NDCs) and the province/city pilot carbon markets. Assuming that China will set provincial targets for meeting its NDCs for reducing carbon intensity per unit energy and its carbon market targets carbon intensity per unit GDP, provincial and urban governments will need to determine the level of urban emission reductions given the concentration of energy and economic activity in Chinese cities. As policymakers evaluate specific interventions and whether they should be implemented at the urban or provincial scale, it will be important to compare across multiple objectives (e.g. carbon, air pollution, cost reductions). If the air quality implications of reducing carbon and energy intensity are being considered, then policymakers will also need to understand what the distribution of air quality benefits are from urban and non-urban emission reductions. Because air quality benefits are dependent on the location of the emission reductions, comparing across strategies will require tools that can distinguish between urban and non-urban emission reductions.

Various tools exist that can estimate the implications of land use, technology, policy and behavior change strategies for reducing carbon emissions in urban areas. Land Use-Urban Planning models (UrbanFootprint 2013) can estimate the impacts of compact urban development and other land use strategies for reducing building and transportation sector emissions, but can only estimate emission changes within cities and are limited in their ability to estimate air pollution/health benefits beyond national average $/ton emission reduced estimates. Urban carbon emission inventory and climate action planning tools (e.g. ClearPath, CURB, CyPT) acknowledge the co-benefits of reducing carbon emissions, but are generally only able to qualitatively assess the benefits of particular interventions. If they do attempt to quantify the air pollution benefits, they are limited to linear functions relating carbon and air pollution that are unable to take into account the nonlinear dynamics of air pollution formation and transport. Lastly, integrated assessment models, such as GAINS (Wagner et al. 2018), have aligned air pollution and carbon emission inventories so that interventions can be evaluated across multiple objectives (e.g. carbon, air pollution, cost). IAMs are generally limited by the spatial scale of gridded carbon/air pollution emission inventory and the simplified source-receptor matrix simulating a full-scale air pollution and transport model. The CFAD model used in this study couples the carbon/air pollution emission inventories at the urban scale with a air pollution dispersion model to estimate the distribution of air quality changes resulting from urban interventions.

For local and regional policymakers, there are few tools that are able to evaluate carbon, air pollution, and health co-benefits at the urban scale. This work will utilize this new prioritization tool to explore the multiple benefits (carbon, air pollution, cost) of different urban infrastructure strategies to determine the tradeoffs between strategies in the context of co-benefits. First, then air pollution/health benefits of urban energy efficiency and end-of-pipe emission control strategies are compared across 15 cities in the Jiangsu province in China. Once the intercity variability of these benefits is determined, a comparison of the capital costs and energy savings of each strategy are used to evaluate life cycle cost. Lastly, we compare the health benefits of each strategy to the costs to determine how policymakers should evaluate tradeoffs between urban strategies in the context of complying with carbon mitigation targets.

Previous work (Liu et al. 2016) has utilized air pollution-chemical transport models to evaluate the effectiveness of regional air quality interventions, however these models are too complex, sophisticated to be run effectively at the city-scale (<1km). This study utilizes the Carbon

Footprinting and Air Pollution Dispersion (CFAD) model to couple city-wide Scope 1 and 2 carbon emissions at the urban scale with an air pollution dispersion model (AERMOD). Most cities reporting carbon emissions account for scope 1 (in-boundary emissions) and scope 2 (energy-related carbon emissions embedded in transboundary energy infrastructure) and it is necessary to account for these emission sources so that the associated PM2.5 emissions can be delineated between urban and non-urban sources. AERMOD is chosen as a computationally inexpensive and spatially-resolved air pollution transport model that can be integrated with carbon and air pollution emissions at the city-wide scale. Alignment of the carbon and air pollution emissions across all cities within each province uniquely allows the model to evaluate the urban and non-urban emission implications of urban-specific strategies to reduce energy use and emissions applied (such as waste heat to district energy).

2. Methods

The prioritization tool provides a basis for evaluating infrastructure interventions across coupled carbon, air pollution, and health benefits. It uses a cost effectiveness basis, per unit CO2 or premature mortality avoided, to evaluate policy interventions across multiple metrics. Policy targets, such as carbon emission reduction targets and air quality improvement targets, are used to set objectives for the prioritization tool across multiple interventions. The interventions are evaluated based upon their abatement potential and cost metrics (first cost, life cycle cost, life cycle cost + health benefits), where first cost encompasses the capital and operations & maintenance costs of a given intervention and life cycle cost consists of first costs with annualized energy savings. Health benefits within cities and across the province associated with reductions in urban PM2.5 emissions are calculated using the CFAD model described below, which estimates the reduction in premature mortalities due to PM2.5 at multiple spatial scales.

To reduce air pollution concentrations at the urban scale, there are two types of urban air pollution emission control strategies which are being implemented in cities. The most common are end-of-pipe, pollution control strategies (normally seen as command-and-control policies) which aim to decrease or set limits on the air pollution emissions from individual polluters. A second type comes from policies that target activity-use reductions of energy at the facility which lead to direct energy use, carbon, and air pollution emissions reduction by reducing fossil fuel combustion. These policies likely have two distinct objectives (e.g. only the first set of policies directly target air pollution emissions), but both can have significant impacts on urban air quality. Comparing these two sets of policies in cities with known air quality co-benefits (Ramaswami et al. 2017) can verify that urban energy efficiency strategies indeed have comparable air pollution benefits. Cities attempting to mitigate carbon and air pollution should look towards policies that have potential co-benefits, but need tools that will allow them to analyze the tradeoff between different policy options. This work demonstrates the application of a new city-scale air pollution and carbon co-benefits tool to determine the tradeoffs between different pollution control policies with an emphasis on the variability of these benefits in different cities.

Both urban energy efficiency and emission control policies have the potential to achieve health benefits in cities as described in the methodology below. Because the benefits due to reductions in local air pollution are high, more localized, and occur over a shorter time frame; the methods below focus on the quantification of health benefits related to premature mortality for a variety of policy scenarios taking place at the city-scale. The first set of scenarios focuses on emission control policies in the industrial, power, and transportation sectors. These policies reduce air pollution through end-of-pipe pollution controls but do not reduce energy or GHG emissions. The second set of scenarios focuses on urban energy efficiency strategies in the industrial, power, and commercial/residential sectors. These policies reduce both air pollution and GHG emissions through reductions in energy use.

Province Application

Given that Jiangsu is one of the most urbanized provinces in China and has the 4th highest HDI, there is concern that the urban energy efficiency carbon and health co-benefits are overemphasized compared to the typical Chinese city as shown in Ramaswami et al. (2017). Comparing the results in Jiangsu to another less urbanized province with similar population density will clarify whether the distribution of provincial urban and rural health benefits of emission control/urban energy efficiency strategies is more dependent on the economic/emissions distribution within the province or the population distribution. This is critical for policymakers because it will emphasize whether the strategies that maximize health benefits at the provincial level are consistent with those that maximize benefits within cities. Future analysis will apply the same technological assumptions from the six strategies modeled at the urban level to province-wide emissions and carbon abatement targets. We will pay particular attention to whether these strategies applied at the urban scale have more or less province-wide health benefits than if these strategies are applied to urban area specifically. By studying both the Jiangsu province and the Hebei province, we can determine to what extent population density, industrial activity, and urbanization rate influence the distribution of these health co-benefits.

Description of CFAD Model

Previous IAMs (Bollen et al. 2009; Thompson et al 2014; West et al 2013) assess carbon mitigation co-benefits at the national or regional scale but do not have the spatial resolution to assess changes in air quality resulting from urban actions. Models targeting co-benefits such as GAINS may adapt their grid cells based on population density and urban extent to estimate the additional air pollution exposure that takes place in cities on top of background regional concentrations, but have difficulty differentiating between urban and provincial emission reductions (Liu et al. 2019). State-of-the-art air pollution models such as CMAQ and WRF-Chem can be adapted to specific city regions (Liu et al. 2016), assuming the necessary emissions, spatial location, and meteorology data is present, but cannot assess co-benefits. Most state-of-the-art air pollution models struggle with the tradeoff between spatial granularity and processing time, which is why new models such as CFAD have been developed.

The twin challenge of reducing both local air pollution emission of PM2.5 and CO_2 emissions can be addressed through urban energy efficiency strategies that reduce urban energy use related to infrastructure activity. The Carbon Footprinting and Air Pollution Dispersion (CFAD) model uses city-specific carbon and PM2.5 emission data across 600+ urban areas in China (Ramaswami et al. 2017; Tong et al. 2018) related to energy use from homes, businesses, industry, transport and power generation to assess the health benefits from urban emission reductions. Because it utilizes bottom up data and models of energy-use activities occurring in individual cities, CFAD is able to model urban-specific emission mitigation strategies whereas most models can only be applied to provincial-level strategies.

The health benefits of urban energy efficiency and emission control policies across sectors at the urban scale may be variable due to changes in economic structure and population across multiple cities. Therefore, cities of various sizes across one province in China are used to estimate the change in climate and health benefits based on changes in emissions and the concentration of PM2.5. Chinese cities provide an interesting application for this type of model because of the air pollution and carbon policies that are being designed to reduce both of these environmental stressors. At the same time, the high concentration of population, economic activity, and pollution make urban centers susceptible to health risks related to ambient air pollution while also key players in any pollution mitigation strategy. Jiangsu (including Shanghai) provides a useful case study due to the concentration of people, industrial activity and wealth in its urban agglomerations. Air pollution levels remain high due to industrial and transportation activity, however the power sector has achieved significant emissions savings due to advanced pollution controls.

The CFAD model assesses energy use by fuel type and estimates carbon/primary particulate matter emissions at the city-wide scale while assuring consistency with provincial emissions by balancing urban and rural emissions throughout a province. This establishes emission inventories occurring both within and outside the city; allowing for the estimation of the impact of provincial or regional emission reduction policies compared to urban only emission reduction policies. The location of transportation, industrial, and residential/commercial emissions sources are allocated to urban areas based upon their administrative boundary. Air pollution dispersion modeling (AERMOD) is then run at the provincial level to estimate changes in concentration and exposure throughout the urban areas across a province. This modeling architecture allows for the estimation of changes in air pollution exposure due to individual carbon mitigation and air pollution mitigation policies through scenario assessment. Calculating the health benefits in each city requires an estimation of change in pollution exposure of the residents of each city based upon the change in PM2.5 concentration, which has well established health risk functions due to chronic exposure.

The model is able to process scenarios ranging from cross-sectoral strategies such as waste heat exchange, which require co-location of industrial, residential and commercial buildings likely to occur only in cities compared to single-sector strategies such as industrial energy efficiency improvement and/or pollution abatement controls, which may be implemented within urban areas or at the provincial-scale. Previously the CFAD model focused on determining the change in air pollution and carbon emissions due to urban energy efficiency actions that could take place at the city-scale (both single sector and cross sector) and the resulting changes in air pollution concentrations due to these interventions. Adding additional scenarios of emission reduction due to air pollution control strategies enables a comparison between policies directed at air pollution control primarily compared to policies that address carbon but have air pollution co-benefits. A retrospective, What-if analysis is used to develop emissions reduction scenarios for 6 strategies (see Table 2-1); these reduction scenarios are conceived based on policies in the 12th Five Year Plan (Ramaswami et al. 2017) and estimated based upon the reduction that could have occurred in 2010 in cities across the Jiangsu province.

Scenario Development

The scenarios are developed based upon 2010 energy use data (Tong et al. 2018) for the 13 cities in the Jiangsu province. Given the hazardous air pollution episodes of the past 10 years in China, the national government has developed multiple policies through the 12th and 13th Five-Year Plan and associated environment and energy directives to reduce air pollution in the power, steel and cement, and transportation sectors which are used to inform the Emission Control strategies. Urban Energy Efficiency strategies are developed for the power, industrial, and residential/commercial buildings sectors using the CFAD model. The What-If scenario represents a picture of 2010 energy use and emissions in China, while the strategies below are built with the expectation of deployment by 2020. Therefore, emissions control equipment, industry and building efficiency assumptions may seem conservative, but are based on policies to be implemented in the short-term. The assumptions used to determine the emission reduction of each policy scenario are detailed in the SI.

Emission Reduction Scenarios are developed to evaluate the health benefits of each individual urban energy efficiency and emissions control scenario based upon current policies and previous literatures estimating the adoption of new industrial efficiency/emissions control equipment (Zhao et al. 2014; Lei et al. 2011). Emissions inventories in Jiangsu show industrial, residential/commercial heating, and transportation sectors contributing the majority of PM2.5 emissions (Wang et al. 2015), so the scenarios developed target these sectors. Health benefits are determined by the expected change in urban PM2.5 concentration under each scenario.

STRATEGIES IMPLEMENTED AT THE URBAN SCALE

Emission Control	Urban Energy Efficiency
PowerPlant/Steel/Cement Controls	Industrial Efficiency
PowerPlant (PP) Controls only	Building Efficiency
Vehicle Fuel Standards (China III – V)	Waste Heat Exchange – District Energy

Table 3-1 Organization of Scenarios into Emission Control and Urban Energy Efficiency Categories

Modeling Approach

Annual changes in carbon and PM2.5 emissions at the city scale are used to estimate the costs and benefits of the six policy scenarios. Scenarios are run across cities in Jiangsu based upon 2010 energy use and activity data (Tong et al. 2018) to determine how city-wide emission inventory changes. These changes are input into CFAD model to determine PM2.5 concentrations in each city under each scenario; these resultant concentrations are compared to baseline 2010 PM2.5 concentrations. Costs of each policy scenario are calculated as discussed below, while health benefits due to reductions in premature mortality risk are calculated based on the difference in PM2.5 concentration in each scenario compared to the baseline.

Retrospective analysis is used to develop emissions reduction scenarios for 6 strategies: 3 urban efficiency and 3 emissions control strategies – these reduction scenarios are built based on policies to be implemented in the 2010-2020 period (Ramaswami et al. 2017); the change in CO2/PM2.5 emissions is estimated based upon the reduction that would have occurred in 2010 in cities across the Jiangsu province. By analyzing six scenarios separately to estimate the change in emissions for each city across the province, the variability of each policy can be ascertained along with the overall effect of each policy across the province. By using this type of scenario analysis we can predict which policies are more effective air pollution and carbon mitigation strategies relative to one another without attempting to predict the economic, industrial and migration patterns that may occur in the cities in the future.

Cost Benefit Evaluation

Costs for each policy are estimated based on the technologies that need to be installed or implemented in order to reduce emission improve efficiency. Pollution control costs are estimated using the GAINS-China model (Amann et al. 2008) and urban energy efficiency policy estimates are within the range estimated by ESMAP (2013). Both urban energy efficiency policies and air pollution control policies are likely to be instituted in a top-down manner in order to account for the fact that the societal benefits of these actions will likely not benefit the industries bearing the majority of the costs. Therefore, cost effectiveness will likely not be utilized to compare across policies but rather to compare to a national or regional set of strategies that meet a certain cost accounting limit. While we acknowledge that net costs/benefits through CBA is one metric by which to compare the efficiency of policies with health-related impacts, all the policies we've examined show current or future net benefits; so, the ratio of costs/benefits is a more likely standard by which these policies could be evaluated by decision-makers.

Because the costs of each policy are scaled on different functional units ($/ton CO2, $/ton PM2.5 reduced), comparison across policies is based upon cost effectiveness using a cost-benefit ratio (CBR) rather than through cost-benefit analysis (CBA) of the net benefits of reducing PM2.5 in each policy scenario. The cost-benefit ratio is utilized to compare the efficiency of each policy on a per unit health basis. Policies are compared using a cost-benefit ratio to determine which policies are most cost effective in reducing premature mortality and to compare to cost effectiveness of other health-related policies (Viscusi and Aldy 1992).

Previous cost-benefit estimates of air pollution controls in the US (EPA 2011) show that benefits related to $PM_{2.5}$ reduction generally account for the majority (>90%) of the premature mortality benefits. While others have focused on differential morbidity effects of air pollution (Hsiang et al. 2017, Wu et al. 2017), we use premature mortality resulting from chronic exposure to PM2.5 levels as an indicator of changes in urban benefits of pollution reduction. For comparison, the social cost of carbon is used to estimate the benefits of CO2 reduction for comparison, assuming these costs are constant globally. Because these carbon and air pollution emissions are concentrated in cities, we evaluate carbon and pollution control strategies at the city-scale to compare health benefits from both at the same spatial scale.

Policy Targets for Urban Emission Reduction Scenarios

Evaluation of the policy scenarios takes place along two objectives, maximizing carbon abatement potential and maximizing PM2.5-related premature mortalities avoided. Carbon abatement targets are developed based on China's nationally-determine contributions for 2030 and the current targets of the Shanghai and Jiangsu Emission Trading Schemes. Based on carbon intensity targets per unit energy (tCO2/tce) and per unit GDP (tCO2/RMB), 2020 and 2030 carbon abatement targets were developed for all urban areas across the province which would require 41-77 MMT CO2e to be reduced annually by 2030. Air pollution standards in Jiangsu are based on Class 2 standards (<35 µg/m3) which Jiangsu has been in compliance with for 60-70% of the time since 2013 (Liu and Gao 2018). As one of the most developed provinces in China, Jiangsu already has strict air pollutant emission control technologies on its power plants, but no specific emission reduction targets.

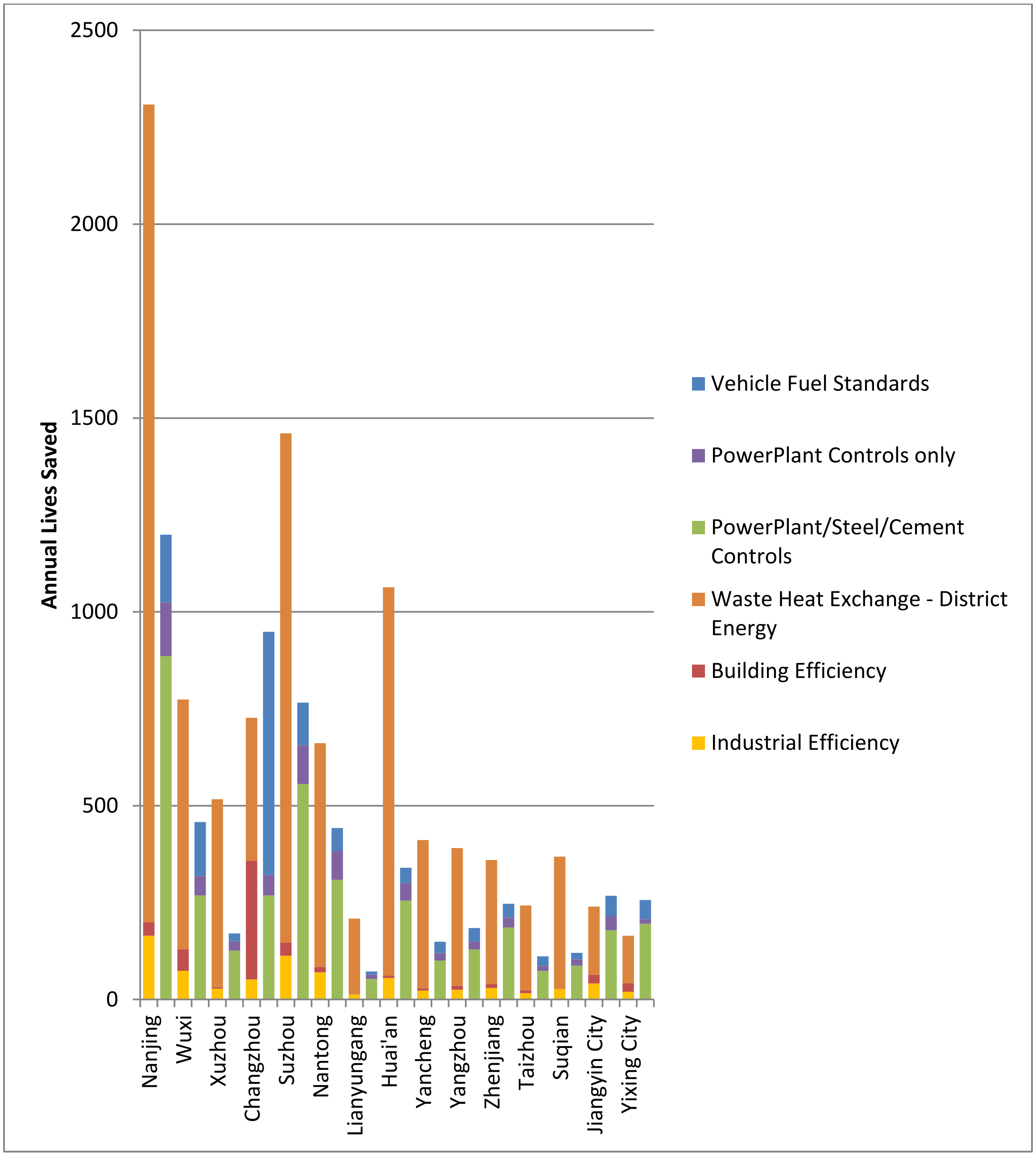
3. Results

Health Benefits of Pollution Control and Efficiency Policies

Figure 3-1 shows the health benefits (million RMB) of PM2.5 emissions avoided in each scenario across all cities in the Jiangsu province. For all cities, waste heat exchange and industrial emission controls show the greatest aggregate health benefits (annual premature mortality avoided) ranging from 100-500 annual premature deaths avoided. This is likely due to the high proportion of industrial and residential emissions in the urban emission inventories. Changzhou is one of the few cities showing high health benefits due to building efficiency and vehicle fuel standards (likely due to its highly commercial economy). It’s clear that no one policy is most effective across all cities, but that waste heat exchange – district energy has large health benefits across almost all cities. Health benefits of each strategy are highly dependent on the economic and emissions characteristics of each urban area.

For certain cities, emission control and urban energy efficiency policies have similar health benefits due to similar changes in emissions in key industrial sectors. As expected, cities with high amounts of industrial waste heat that can be used for heat exchange, for example, Nanjing and Suzhou, also have high amounts of industrial pollution that can be mitigated by power plant, steel and cement controls. For most cities, expected pollution controls show >100 annual premature mortalities avoided from industrial emission control strategies and <100 for powerplant and vehicle fuel standards. Across most cities, vehicle fuel standards show greater health benefits than powerplant controls, likely because powerplants already have a high level of control technology. Waste heat exchange shows greater benefits than industrial efficiency because of the replacement of dirtier heating fuels and less efficient boilers in residential and commercial buildings. Industrial efficiency shows higher health benefits than building efficiency because of the large amount of industrial energy and emissions avoided, but building efficiency has higher health benefits per unit avoided emission (see Table 3-2). Variability exists in the health benefits of each policy at the city scale due to the differences in the sectoral contribution of PM2.5 emissions in each city. This indicates that even though policy mandates may be developed and implemented at the national or provincial level, careful attention should be paid to how these policies are applied in cities to maximize air pollution benefits.

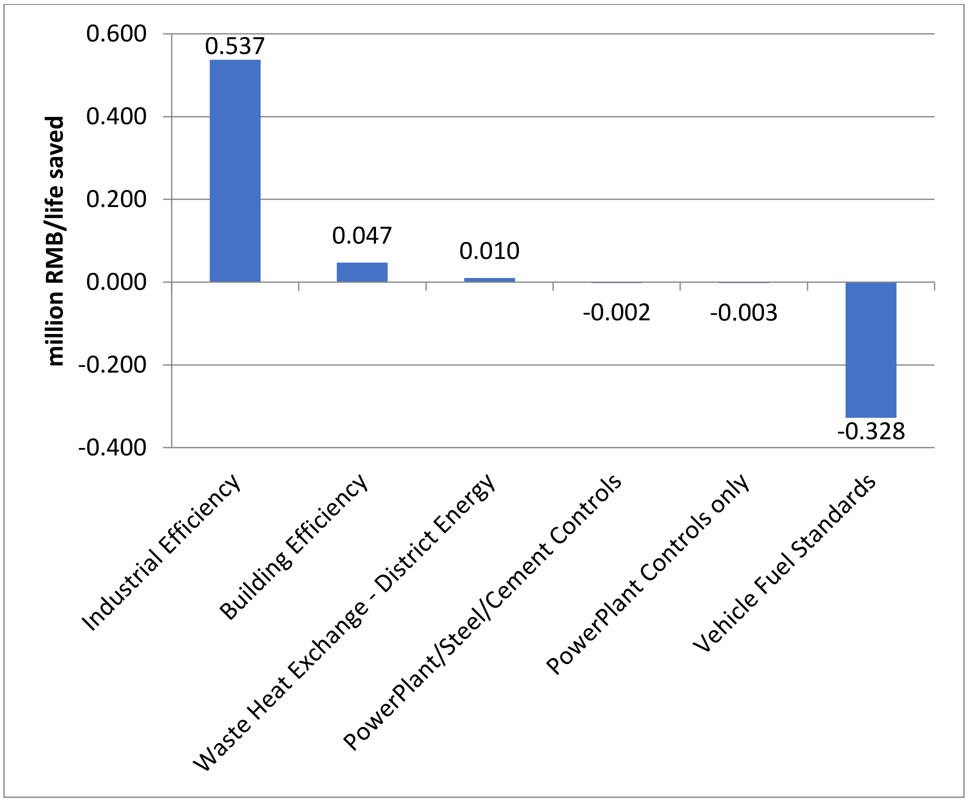
Figure 3-1 Annual Premature Mortality Avoided across Six Urban Energy Efficiency and Emission Control Strategies



Policy Cost-Effectiveness

Figure 3-2 shows the life cycle cost (including capital and implementation cost, and energy savings) of each strategy across the 15 cities scaled by the estimated premature mortality avoided due to air pollution reductions for each scenario. This cost effectiveness metric ($/life saved) indicates that urban energy efficiency policies could achieve similar benefits at lower cost. If comparing strategies on a pure cost basis, vehicle fuel standards have the highest implementation cost per life saved. Figure 3-3 shows the aggregate health benefits in terms of premature mortality avoided compared to the variability in marginal cost of the strategies in terms of cost per premature mortality avoided, where cost is defined as the difference between the capital costs required to implement the policy minus the energy savings in each city. These results show that waste heat exchange, industrial efficiency, powerplant/steel/cement controls have the highest aggregate health benefits and on a first cost basis emission control strategies are less per unit life saved, but on a life cycle basis all urban energy efficiency policies are cost positive when accounting for energy savings. Table 3-2 indicates that the health benefits of each emission control strategy outweigh the costs on a per ton emission reduced basis.

Figure 3-2 Policy Cost Effectiveness (per life saved)



* Negative numbers indicate costs are greater than energy savings per life saved

	Cost	*Energy Savings*	*Health Benefits*
Urban Energy Efficiency (per ton CO2)			
Industrial Efficiency	-64	92	6
Building Efficiency	-572	563	225
Waste Heat Exchange – DE	-38	797	129
Emission Control (per ton PM2.5)			
PP/Steel/Cement Controls	-88	--	60,421
PP Controls	-125	--	49,794
Vehicle Fuel Standards	-61,018	--	186,241

Table 3-2 Net Benefits of Urban Energy Efficiency Policies (per ton CO2/PM2.5 reduced)

Comparison of Carbon and Health Benefit Potential using Marginal Abatement Cost Curves

While Figure 3-2 compares all six policy scenarios of a health basis, Figure 3-3 goes a step further to compare the urban efficiency actions along both their unit costs and potential for reduction in premature mortality. Table 3-2 disaggregates the energy reduction and health benefits of urban energy efficiency strategies on a per unit CO2 reduced basis, demonstrating that the health benefits ($/ton CO2) are 2-5 times more than the SCC at $40/tonCO2. Previously these health benefits have only been compared to the SCC and MAC at the national level, these results at the urban scale are more pronounced because of the concentration of residential and transportation emissions in cities and localized effects of PM2.5. The cost of carbon mitigation (MAC) is positive similar to Hamilton et al. (2017) due to the projected energy savings, but even without these energy savings the health benefits of urban energy efficiency strategies likely outweigh the unit costs of emission reduction.

Figure 3-3 Marginal Costs vs Annual CO2 and Premature Mortality Reduction Potential

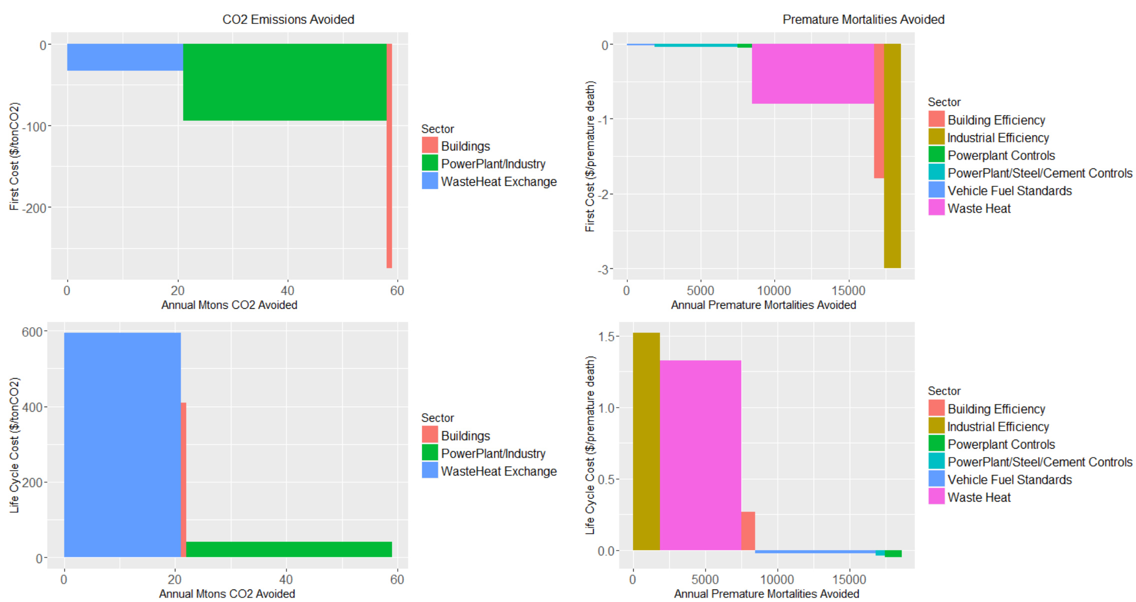


Table 3-3 summarizes the strategies that should be prioritized depending on the objective of local and provincial policymakers with respect to meeting carbon mitigation and air pollution targets based on the abatement curves detailed in the Supporting Information. Strategies are prioritized based on first cost, life cycle cost, and life cycle cost with health benefit on the same basis ($/ton CO2 reduced, $/premature mortality avoided). First cost compares the capital costs implementing each strategy while energy savings and health benefits are added on to determine the net benefits of each strategy per ton CO2 avoided or life saved. The policy goals refer to the carbon abatement potential and premature mortality abatement potential needed from the suite of strategies to reach targets. Waste heat exchange is the preferred policy across first cost, life cycle cost, and life cycle cost+ health benefits optimizations due to lower capital costs, high degree of primary energy savings from reduced heating fuel use, and the higher relative benefit of reducing low-level PM2.5 emissions from the combustion fossil fuels. There is no difference when selecting for urban health benefits versus province-wide health benefits, likely due to the fact that PM2.5 exposure is concentrated in urban areas where >60% of the population resides. Emissions control strategies are more cost-effective when maximizing premature mortalities avoided on a first cost basis, with vehicle fuel standards being preferred due to their higher health benefits per ton PM2.5 pollution reduced. When maximizing health benefits but optimizing for life cycle cost rather than first cost, the urban energy efficiency strategies become more cost effective due to the energy savings of each strategy. Industrial efficiency is preferred over the other strategies due to the higher primary energy savings per premature mortality avoided.

Table 3-3 Summary of Preferred Urban Energy Efficiency Strategies

Primary Goal	Ranked Prioritization across 6 Strategies ($/ton CO2 reduced or $/premature mortality avoided)					
	1	2	3	4	5	6
40 MtCO2/year Abatement – Minimize First Control	Waste Heat	Industrial Efficiency	Building Efficiency	--	--	--
40 MtCO2/year Abatement – Minimize Life Cycle Cost	Waste Heat	Building Efficiency	Industrial Efficiency	--	--	--
40 MtCO2/year Abatement – Minimize Life Cycle Cost + Maximize Urban Health Benefits	Waste Heat	Building Efficiency	Industrial Efficiency	--	--	--
40 MtCO2/year Abatement – Minimize Life Cycle Cost + Maximize Provincial Health Benefits	Waste Heat	Building Efficiency	Industrial Efficiency	--	--	--
Maximize total lives saved – Health Benefits at lowest cost (first cost)	Vehicle Fuel Standards	PP/Steel/ Cement Controls	PP controls	Waste Heat	Building Efficiency	Industrial Efficiency

Maximize total lives saved – Health Benefits at life cycle cost	Industrial Efficiency	Waste Heat	Building Efficiency	Vehicle Fuel Standards	PP/Steel/ Cement Controls	PP controls

4. Discussion

The prioritization tool shown here provides evidence for policymakers looking to evaluate urban infrastructure interventions based on coupled carbon and health benefits. The tool show here allows for the ranking interventions per unit CO2 avoided or per unit premature mortality avoided along first cost, life cycle cost, and life cycle cost/health benefits metrics. Waste heat to district energy is the first choice on a first cost, life cycle cost, and life cycle cost+health benefits for cities in Jiangsu looking to reduce carbon emissions and meet climate policy targets. This emphasizes the need to consider circular economy strategies, such as waste heat exchange, that could have low cost, high energy savings, and large health benefits. Industrial Efficiency is the first choice when seeking to maximize premature mortalities avoided on a life cycle basis (due to energy savings), while vehicle fuel standards are the first choice on a first cost basis (due to the larger benefits of ground-level reductions in emissions). These comparison highlights the prioritization tool's ability to compare strategies across multiple objectives (e.g. carbon and air pollution/health benefits) based on multiple metrics (e.g. monetized cost, energy savings, and urban/provincial health benefits).

As decisions on urban energy efficiency interventions are made, there is a need for tools that compare the benefits of urban/non-urban emissions reductions. More important is the determination of regional strategies for reducing pollution. For example, many cities require coordination with neighboring communities in order to manage air quality effectively. Reducing emissions in the city may also benefit neighboring cities and improve air quality across the province. Therefore, tools must be able to account for the distribution of health benefits across cities and their hinterlands.

This work demonstrates that the policy preferences of cities may differ depending on whether the cost effectiveness ($/life saved), marginal benefits ($/ton emission reduced), or abatement potential (aggregate CO2 reduced, aggregate lives saved) are the metric prioritized. The marginal benefits per unit CO2 avoided are greatest in the building efficiency and waste heat exchange strategies, however the abatement potential of both the industrial efficiency and the waste heat exchange strategies is far greater in our scenarios. In addition to both industrial efficiency and waste heat exchange being cost positive due to energy savings, industrial efficiency strategies maximize carbon abatement while waste heat exchange maximizes premature mortality avoided. Our health benefit estimates ($/tonPM2.5 avoided) appear conservative compared to previous estimates in the US context ranging from $140,000-400,000/ton PM2.5 (Fann et al. 2012) for the same sectoral strategies. Our health co-benefit estimates ($/tonCO2 avoided) also appear conservative falling between the national $70-150/tonCO2 (Hamilton et al. 2017) and the China-specific $70-840/tonCO2 (West et al. 2013). Our estimates may underestimate the health benefits of elevated emissions sources (e.g. powerplants and industry) because these benefits of these high stack sources will be distributed beyond the urban boundary.

Broadly, this methodological framework furthers the science of understanding local air pollution problems in cities while exploring ways to quantify local health benefits in comparison to carbon costs and benefits. Specifically, the model allows for the estimation the health co-benefits of urban energy efficiency policy in Chinese cities using the Jiangsu province as a case study. The first key point is that variability exists in the health benefits of each policy across the 13 cities. Therefore, while air pollution policy may be implemented at the national or provincial level in China, benefits should be measured at an urban scale to accurately assess the results of improved air quality. Second, in comparing potential air pollution reduction policies, conventional air pollution controls and energy efficiency in industry may produce the highest aggregate benefits, but waste heat exchange replacing residential heating fuels will achieve similar health benefits. All policies appear cost-neutral or cost-positive (less than 3,000 RMB/life saved) except for vehicle fuel standards. All policies except for vehicle standards show benefits (energy savings/premature deaths avoided) outweigh policy costs in year 2010, vehicle standards are expected to have positive net benefits as the Chinese vehicle market grows (ICCT 2010, 2014)

Circular Economy Strategies

The algorithms and data underlying the waste heat to district energy strategy in each city are detailed for 600+ Chinese cities (Ramaswami et al. 2017) and specifically for the Hebei and Fujian provinces (Tong et al. 2017; 2018). In order to ensure a conservative estimate of the potential for waste heat reutilization through 4th generation district energy systems, we only consider densely built-up, urban areas of Chinese cities (not all city households) in determining the heat demand of residential/commercial buildings. Urban areas of the city administrative areas cover a minimum of 60% of the households in cities in Jiangsu. Our estimates of heating demand depend on the urban residential/commercial floor area and heating energy use intensity based on climate zones. Based on other studies that indicate low-grade waste heat can be economically-feasible and efficiently conveyed over fence line distances up to 30 km (UNEP 2015). Although the distance between industrial facilities and population centers is a potential obstacle in the US and Europe for district energy-waste heat exchange, many urban population centers in China also house large industry clusters partially due to the economic and technological development zones in Chinese cities. According to guidelines for European district energy systems (Moller and Werner 2016), 4th Generation District Energy Systems are feasible above heating demand density >30 TJ/km2 and highly feasible above 300 TJ/km2. Heating demand density across all cities in the Jiangsu province are above 300 TJ/km2, indicating district energy is highly feasible in these cities.

AERMOD Limitations

The CFAD model utilizes a dispersion model to estimate changes in PM2.5 concentrations due to changes in primary PM2.5 emissions. Secondary PM2.5 and background PM2.5 are not considered in this study, as we expect these to be less variable across cities. CFAD only takes into account changes in Primary PM2.5 concentration and may underestimate the improvements of air quality based upon these 6 policies; however, this also underestimates the baseline concentration in each city, but since the shape of the concentration response function is sublinear – we may be underestimate the change in relative health risk. We have confidence that we are not overestimating the response to urban changes in emissions because in comparisons with the GAINS-City Model (Wagner et al. 2018) the AERMOD dispersion model showed more muted changes in urban emissions likely due to the increased influence of transboundary pollution from non-urban areas outside of the city (which is held constant in our analysis).

5. Conclusion

This study provides a methodology for addressing co-benefits at the city scale in China. It particularly highlights the variability that exists in the health benefits (defined as number of premature deaths avoided) of each policy at the city scale. This indicates that even though policy mandates may be developed at the national/provincial level, careful attention should be paid to how these policies are implemented at a city-scale due to difference in the population exposed and the emissions sources in each city. Results indicate that waste heat exchange and industrial efficiency/emission control can decrease premature mortality significantly, but only urban industrial efficiency and waste heat exchange reduce both air pollution and carbon damages. Further urban efficiency strategies are most cost effective due to the associated energy savings. Health benefits generally exceed carbon benefits, among policies that reduce both carbon and PM2.5. Cost effectiveness indicators ($/life saved) indicate that urban energy efficiency policies could achieve similar air pollution benefits at lower cost.

While carbon benefits will be globally distributed, China is already taking steps to reduce and peak its carbon emissions by 2030 through its Nationally Determined Contribution and national carbon trading scheme. Adding health benefits to the industry-specific abatement curves which govern the expected cap on carbon emissions may change optimal total cap or industry-specific carbon limits. However, a more prominent question, given the high pollution levels and high urbanization rates in China, would be how much urban air pollution is reduced by carbon market and industrial efficiency policies? If this is indeed the question, then local and provincial governments should seek carbon policies that maximize air pollution reduction and health benefits and compare these benefits to the mandated air pollution control policies.

Policies that target carbon mitigation and air pollution may have synergistic effects if energy use reduction and a move towards cleaner burning fuels are part of both strategies. In the absence of certain benefits, cost minimization of these policies is the easiest way to ensure policy design will achieve the optimal level of social welfare. For cities, we focus on policies that will have certain, localized health and energy savings benefits, which require a more nuanced approach to comparing benefits across different energy efficiency and emission control policies. One approach is to evaluate each policy based on those that achieve the greatest health benefits, which will promote policies that reduce the maximum amount of emissions or energy use. A second approach is to evaluate policies based upon their cost effectiveness, to maximize the ($/life saved) of the policies. We compare these 6 policies across both maximum health and maximum cost-effectiveness to determine how much these depend on city-specific emissions and meteorology. Then based on the marginal abatement cost of carbon reductions, we can compare these benefits to typical climate benefits estimated by national MACS.

Cities grappling with air pollution challenges may have national or provincial air quality targets, but the policies which would effectively reduce air pollution vary greatly even among cities in the same province. Results of this work indicate a need for city-scale air pollution emission inventories and for regional emission control strategies to be tailored to differences in emissions of each city and also differences in the contribution of urban and rural emissions to regional air pollution. Policies effectively reducing urban PM2.5 levels would still need to be implemented at a provincial or regional scale due to pollution transport and the contribution of transboundary emissions, but the health benefits of these policies should be measured at the city-scale given the high population and high air pollution levels. Future work should focus on assessing the contribution of external emissions and emissions reductions to changes in urban air pollution levels in order to ascertain the benefit of urban only mitigation strategies. Further studies could assess if morbidity benefits such as those highlighted in (Wu et al. 2017) are similarly variable across provinces and if these change proportionally with implementation costs.

Chapter 4 – Fine-Scale Air Quality Models for Assessing Social Justice in the context of Local Carbon Mitigation Actions

1. Introduction

Cities have multiple objectives in their management of air quality issues. First, they seek to improve public health and quality of life by improving air quality and more consistently track health impact metrics to evaluate public health outcomes (Martenies, Wilkins, and Batterman 2015). Quality of Life benefits to reducing these air pollutants is evidenced by numerous studies that have documented spending by citizens for defensive instruments against pollution (Zhang and Mu 2018; Deschênes, Greenstone, and Shapiro 2017). To do this requires an understanding of the management of emissions sources that will maximize air quality benefits across the city. Secondly, cities know that there are concentrated areas of pollution in and around low-income and minority communities (L. J. Cushing et al. 2016; Clark, Millet, and Marshall 2014) and therefore are concerned with reducing pollution across the city and within certain neighborhoods. Therefore, many cities with air quality management plans also seek to reduce pollution levels in these hotspots. While these two objectives seem aligned, the policy interventions and models used to analyze their impacts may be different.

In order to manage air quality at the urban scale, cities may be concerned with a variety of air quality metrics. Public and regulatory concern over the number of days with unhealthy air quality (due to events such as wildfires or inversions) indicate a need to measure acute air pollution episodes and limit their occurrence. Cities may also be concerned with temporal variation in these episodes. For example, unhealthy air quality levels could occur during different hours of the day (e.g. during rush hour/congestion) or at different times of the year due to seasonal variations in weather patterns (e.g. wind and inversions) and human activity (e.g. crop burning, heating of homes). For the purposes of this study, we focus on the variability in long term exposure to PM2.5 due concentrated areas of pollution within cities. This variability has significant implications for equity and environmental justice, which many cities are trying to address (UCS 2019, Bael et al. 2015). In order to formulate evidence-based policy to address inequities in air pollution exposure, fine-scale air pollution models are necessary to connect policy-induced changes in emissions to changes in local, neighborhood-level concentrations.

In order to estimate differences in intracity, neighborhood-level concentration, it is important for air pollution models to report concentration in fine-scaled grids. This is important due to variations in air pollution levels across different neighborhoods (UCS 2019) and because these differences may be contingent on having sufficient spatial granularity to detect air pollution exposure differences (cite Paolella). We know that air pollution exposure will differ within counties, especially those with high population density (Goodkind et al. 2019), but to address questions of equity and environmental justice, it is necessary that air pollution modeling grid size is similar to the census tract or census block size in order to compare demographic data to differences in exposure. If the model resolution is too large, then it will be difficult for differences in neighborhood-level air pollution levels to be determined. There is a tradeoff between model complexity and model resolution and since CTMs (such as CMAQ and WRF-Chem) are so computationally rigorous it may take multiple days/weeks to run (which makes prospective scenarios difficult to assess)

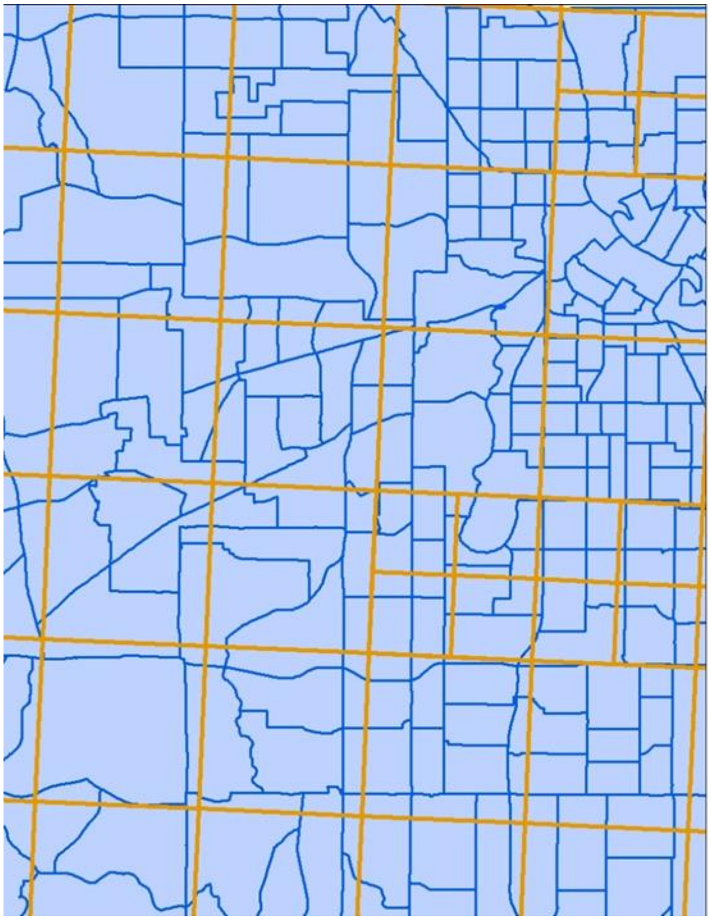


Figure 4-1 Model Grid Resolution (InMap) vs Census Tract Size in Minneapolis

InMap and AERMOD are two models with the spatial granularity necessary to investigate within city variations in air pollution concentrations. Gaussian plume dispersion models (e.g. AERMOD) estimate air pollution levels that are downwind of individual sources or source groups. They are useful for predicting pollution impacts within cities due to nearby sources but are not recommended for predictions of long-range pollution transport (> 50km) (Cimorelli et al., 2005; USEPA, 2015). Reduced Complexity Models (i.e. InMap, AP3, EASIUR) have been developed as less computational alternatives to chemical transport models with InMap specifically being utilized to inform environmental justice issues whereas coarse-resolution models may underestimate exposure disparities among minority and low-income populations (Tessum, Hill, and Marshall 2017; Paolella et al. 2018). The high spatial resolution of InMap in urban areas (up to 1x1 km) allows the model to capture within county differences in pollution exposure at similar spatial size as census tracts, shown in Figure 4-1. Both are computationally inexpensive, allowing users to develop prospective scenarios around multiple policy options. AERMOD is the dispersion model recommended by USEPA for near source air pollution impacts (<50 km) but is limited in its transport processes (only dispersion and deposition) and cannot be used to address secondary PM2.5 formation. InMap has a wider range of transport processes (e.g. advection, mixing, reaction, deposition) but is limited to annual average estimates of PM2.5 and its precursors. Only AERMOD can model diurnal or seasonal variations because it solves for concentrations hourly.

This study compares the two fine-scale air pollution models described above to help inform practitioners of current tools available that can inform questions of equity and provide evidence for emission reduction policies that could have differential health benefits for certain areas within a city. Rather than investigate differences in air pollution exposure, this study is limited to differences in model response as a function of the same emission inventory data (NEI 2014) in the Twin Cities. Comparison between the two models enables us to answer questions related to the transboundary and secondary components of urban PM2.5 concentrations as well as questions of uniform and non-uniform emission reduction intervention benefits across the urban area.
In order to ensure confidence in these reduced complexity tools, they have been compared to monitor data and more conventional models like WRF-Chem (Tessum, Hill, and Marshall 2017). However, the ability for these models to estimate variability within cities needs to be evaluated against tools that regulators currently use to identify pollution hotspots, such as MNRisks in Minnesota (Ellickson et al. 2017). This study uses the case of Minneapolis to investigate the within city variability of AERMOD and InMap with a focus on the following questions. First, we investigate the two air pollution models using the same emission inventory to determine what the differences are in the two fine-scale models. Second, the majority air pollution models either have fine-scale receptor resolution or model secondary formation from long-range pollution; we

investigate the extent to which transboundary pollution coming into the city impacts primary and secondary PM2.5 concentrations within Minneapolis. Lastly, these models are developed to assess the impact of emissions reductions on changes in concentration to estimate marginal benefits of emission changes, so we investigate how the models respond to policy interventions in the transportation and power sector to determine what impact these actions would have on intracity air quality.

2. Methods

Estimates of the marginal benefits of reducing one unit of PM2.5 vary across space, time, and sector. Nationally, EPA has estimated the benefits of air pollution reductions from the Clean Air Act at 234,000 $/ton PM2.5 on average (EPA 2011). Others have estimated that these benefits range from $250 – 41,000 $/tonPM2.5 (Muller and Mendelsohn 2009) across US counties. Further, these benefits are variable based on the sector reducing emissions 48,000 – 510,000 $/tonPM2.5 (Fann et al. 2012) and even vary within sector across states (e.g. 50-872 $/ton PM2.5 from electricity generation reductions in New York) (Shrader et al. 2018). Marginal benefits at the local level also vary up to 10x within the most populous counties according to a recent study using InMap (Goodkind et al. 2019). Therefore, there is a need for fine-scale models that can assess the variability in the benefits of PM2.5 reduction based on prospective policy scenarios. In order to utilize these models, there needs to be a discussion of the various uncertainties that could contribute to this variability in marginal benefits. It is important to distinguish between differences in exposure and concentration; here we focus on the differences in the expected change in concentration at fine-scale (2x2km) model resolution. Critically, we only look at the spatial pattern of changes in concentration independent of the differences in population distribution in order to determine what fine-scale air pollution models can tell us about the changing distribution of air pollution under different emission reduction scenarios.

Assessing the uncertainty in the changes in air pollution exposure predicted by fine-scale air pollution models requires an understanding of spatial scale at which models predict concentrations compared to the uncertainties in the model inputs. Figure 4-2 below describes the models that are able to estimate air pollution concentration within cities and counties compared to the uncertainties in model inputs. Models estimating air pollution at the county-scale must be concerned with uncertainty in model parameters (such as meteorology, topography, wind speed, etc.), the contribution of pollution sources from outside the county (e.g. sources >50km away), and distribution of population within the county both for exposure estimates and emission estimates. At the finer scale, within cities, there is again uncertainty in how emissions are distributed within the city, but an additional question is how well can the models estimate the spatial distribution of changes in concentration? This requires a comparison between models with varying air pollution transport algorithms (e.g. advection, dispersion, formation, mixing, deposition) to determine the modeled response of air pollution concentration to changes in local emissions.

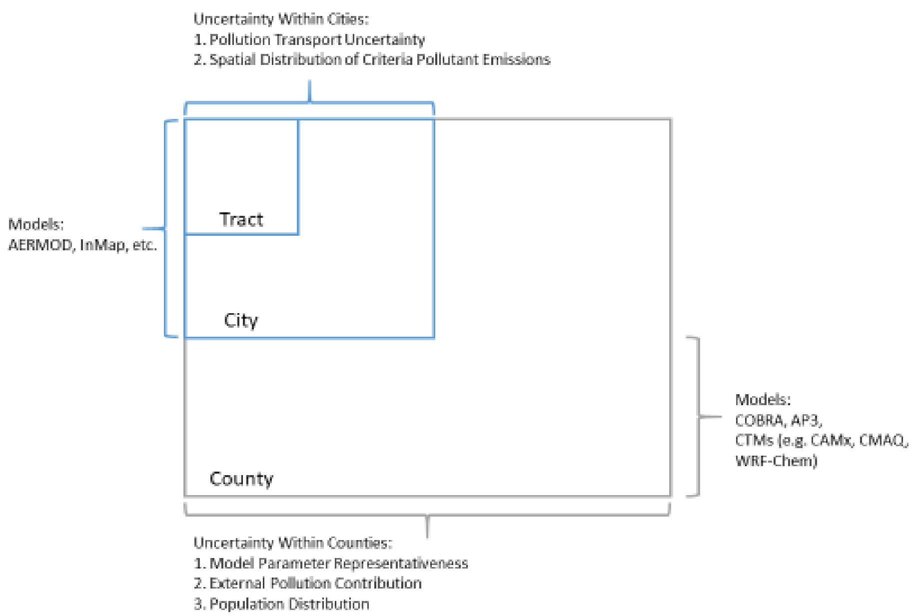


Figure 4-2 Model Uncertainty across Spatial Scale Schematic

Previous studies have been limited in their ability to measure differences in neighborhood level air pollution exposure due to limitations in the coverage of monitoring data, the spatial resolution of air pollution and transport models, and the availability of spatially resolved emission inventories. InMap has been used recently to estimate the inequities in pollution exposure due to vehicle emissions in the northeastern US and California (UCS 2019). Similar studies have been carried out by state agencies (Bael et al. 2019), but have not measured the marginal benefits of emission reduction. Others (Carnell et al. 2019; Zapata et al. 2018; Goodkind et al. 2019) have been able to estimate the marginal benefits of emission reduction due to sector-based emission reductions, but have not been able to tie changes in neighborhood-level air pollution exposure to sectoral emission reductions. Simplified tools, such as COBRA and AP3 (Millstein et al. 2017), have been used in many studies to estimate the reduction in damages due to a given policy at the county-level, but do not have the spatial resolution needed to address differential air pollution exposure within cities or counties.

In order to assess both local primary impacts (near source) and also regional impacts of changes in emissions, air quality management requires an evaluation of both the primary and secondary PM2.5 emission sources (some of which may occur outside the city). State regulators normally use two different types of models to determine how local and regional emissions sources impact local air quality. Dispersion models are used to estimate near source impacts of pollution, while chemical transport models measure regional pollution from sources which may be far outside the city.

To evaluate the potential implications of local and regional PM2.5 emission reductions on concentration hotpots and environmental justice, this study compares two models which can evaluate fine-scale changes in air quality and PM2.5 exposure. While fine-scale air pollution modeling is necessary to account for differential air pollution exposure and health benefits within cities and counties, there is limited consensus on which models are best suited for city-scale exposure assessments. Multiple air pollution models have been used for city-scale exposure assessments (Anenberg et al. 2016; Wesson et al. 2010; Paolella et al. 2018; Gilmore et al. 2019) but have varying degrees of accuracy, application, and spatial resolution. Given uncertainties in the spatial resolution of the emissions and modeling methods necessary to answer air pollution exposure benefits and distribution, it is necessary to compare model outcomes to determine the range of model variability that can be expected in using reduced complexity tools to inform air pollution management policy.

Using two models with known applications to intracity PM2.5 modeling, this study seeks to assess the uncertainties in intracity air pollution exposure assessments. Three particular concerns are sought to be addressed by the study. First, while many models exist most utilize standardized emission inventory data (e.g. US National Emissions Inventory, EDGAR) as inputs which may not have the spatial granularity necessary to investigate intracity pollution exposure, we therefore experiment with the same emissions aggregated at different spatial scales to determine whether the different models respond to the spatial resolution of emission inventories similarly. On top of this, there are questions about the extent to which transboundary pollution sources (e.g. emissions from outside the city) impact air quality within the city, which require the use of emission inventories which separate between urban and non-urban pollution sources. Second, the diversity of models available require an assessment of model architecture to determine how different modeling approaches may have differences in the magnitude and distribution of exposure estimates, even if using the same inventory. Third, many of the models that may be policy-relevant focus on the change in emissions across scenarios in order to model the response to policy, therefore we investigate the response of the models to equivalent changes in the emissions inventory. We focus specifically on whether both models can assess uniform and non-uniform changes in emissions across the city that may be induced by different policies.

Model Comparison

We use the case study of Minneapolis to investigate the response of the two models to changes in emissions across the same study area. Initially, the two model baselines are compared using the same gridded 2014 National Emissions Inventory data. This allows us to compare the initial magnitude and spatial distribution of the two models, to make sure that the response of the model is being compared to similar baseline. If there are any biases in the model architecture, these can be teased out of the initial comparison. Using the NEI data allows us to compare to CTM comparisons as well using the same 2014 emissions inventory scaled to 2017 data at the 5x5km grid scale. AERMOD and InMap are compared at the 2x2km grid scale across 192km MSP metro area to determine how well the baseline matches.

Next two separate experiments are carried out to estimate the response of the models to emission reductions and to transboundary pollution.

To determine the effectiveness of different policies in reducing air pollution concentrations in pollution hotspots (generally located in and around low income and minority communities), one of the key questions is what the effect of reducing nearby sources of pollution is on pollution levels. To investigate, we create three separate emission reduction scenarios. The first consists of a 10% reduction in all emission sources across the study area to determine how sensitive the models are to the same emission reduction. The second scenario investigates a 10% reduction in onroad vehicle emissions, meant to simulate the implications of city-wide emission reductions that aren't targeted at specific locations. The third scenario investigates the implications of targeted emission reductions at high polluting point sources by reducing an equivalent amount of emissions to the transportation scenario. For MSP, this results in the partial or complete shutdown of 3 powerplants in the area, which the local utility has plans to do by 2030. These comparisons allow us to determine whether the spatial differentiation in policy will have a marked effect on areas nearby the affected pollution source and to determine the maximum and minimum distance from the source that will be impacted by primary PM2.5 reductions.

The second set of scenarios investigate the contribution of transboundary wind-blown air pollution into the study area. Using the same 2017 emission inventory data, both InMap and AERMOD are run with only sources within the 192km boundary. AERMOD is then run with all emissions from the rest of Minnesota in addition to the MSP only sources, since it is only expected to be accurate for pollution sources within 50km of the study area (cite EPA). The baseline inventory being run in InMap contains all emissions from the rest of the US and is used as the comparable. The change in concentration compared to the baseline results represents the contribution of regional, transboundary pollution to local PM2.5 concentration. AERMOD and InMap can be compared across primary PM2.5 estimates and the variability in the contribution of transboundary, secondary PM2.5 formation to local air quality can be ascertained from the InMap prediction.

The suite of scenarios allow us to compare how state-of-the-art air pollution models can be used to inform policies targeting air pollution reduction in highly polluted areas. We attempt to ascertain whether there is model agreement in the areas that will see the most benefit from emission reduction and whether any generalizable rules about distance and vector of impact can be determined. An important subtext of all these analyses is whether the uncertainty in model response (due to model architecture) is larger than the spatial uncertainty of emission inventories. If model response is more variable, then perhaps localized emission data and the distance to source proxy is a more meaningful representation of localized air pollution impacts.

Spatial Analysis Methods

AERMOD and InMap outputs are compared across the MSP metro area with standardized grid cells. AERMOD predicts primary PM2.5 concentrations across 2256 grid cells at 2x2km resolution, while InMap predicts primary and secondary PM2.5 concentrations across 404 grid cells at variable resolution up to 2x2km. Because some InMap grid cells may be larger than 2x2km, an area-weighted average of overlapping AERMOD grid cells is used for comparison when necessary. The magnitude and distribution of PM2.5 concentrations in these grid cells is used to determine the relative alignment of the models and their responses to emission reduction.

Of the 404 InMap grid cells, seven are identified as the location of peak ground-level, onroad transportation, or elevated emissions. The distance from these sources to each of the AERMOD/InMap grid cells is calculated to determine how dependent the model response to emission reductions is to the proximity of the peak emission sources.

3. Results

3.1 Baseline Comparison of InMap and AERMOD

As shown in Figure 4-3, AERMOD and InMap generally agree on the spatial distribution of emissions across the Minneapolis metro area. The scatterplot in Figure 4-4 indicates that although there is general agreement, on average the AERMOD prediction is 77% of InMap's primary PM2.5 concentration estimate. However, there is a wider spread at higher concentrations with AERMOD predicting higher peak concentrations than InMap. When running the models with the same emission inventory allocated to the traffic analysis zone, AERMOD predicted much more concentrated pollution concentrations but there was no discernable spatial relationship between the modeled concentrations.

Predicting the contribution of external sources of pollution to the Minneapolis metro area and the contribution of secondary formation required the models to be run with and without emission sources from outside the 192x192 km domain shown in Figure 4-3. Table 4-1 demonstrates that InMap and AERMOD both predict approximately 5-7% of local PM2.5 concentration attributable to outside sources, with InMap estimating that 40% of the transboundary pollution is secondary

PM2.5 formation. The models predict that 82-92% of PM2.5 concentrations are attributable to inboundary sources, with only 11% due to secondary formation on average. The maximum concentration predicted by InMap was in downtown Minneapolis, while the maximum concentration predicted by AERMOD was just to the west of the Allen S. King Powerplant. Interestingly, InMap predicted a larger proportion of secondary PM2.5, likely due to onroad transportation and nonpoint sources dominating emissions in this area.

Figure 4-3 InMap and AERMOD Predicted Primary PM2.5 Concentrations for Minneapolis

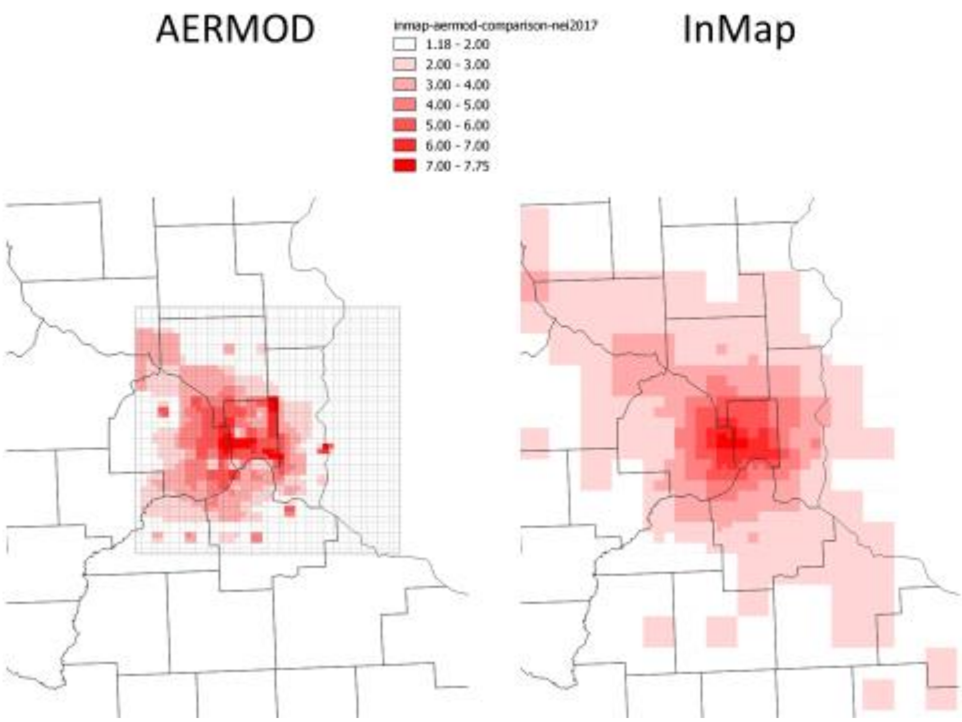


Figure 4-4 AERMOD-InMap Primary PM2.5 Concentration Comparison

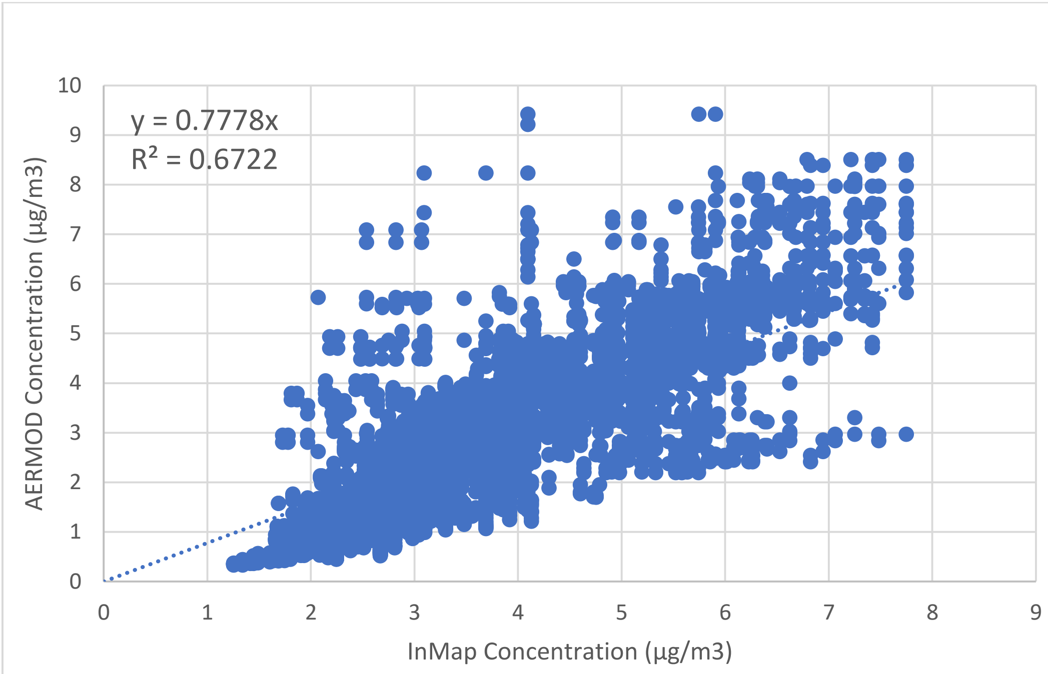


Table 4-1 InMap and AERMOD Secondary and Transboundary PM2.5 Contribution

		Average of all Receptors		Maximum Concentration	
		InMAP	*AERMOD*	*InMAP*	*AERMOD*
Inside Boundary Sources	Primary	82.1% +/- 3.7%	92.5% +/-1.5%	65.6%	98.3%
	Secondary	11.6% +/- 6.3%	--	26.5%	--

Outside Boundary Sources	Primary	3.2% +/- 4.0%	7.4% +/- 0.01%	6.7%	1.7%
	Secondary	2.5% +/- 4.3%	--	1.1%	--

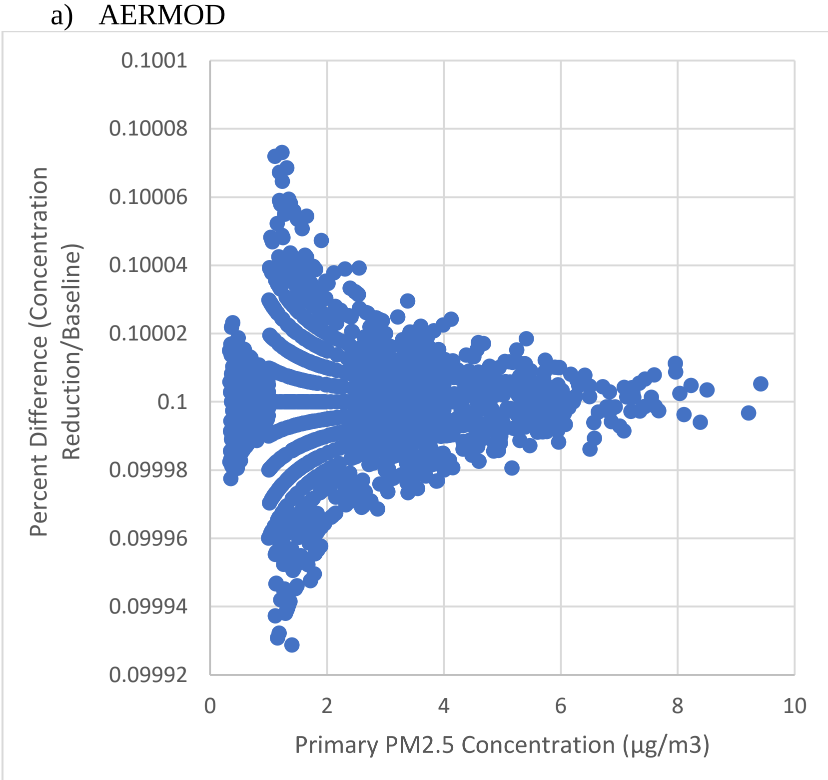
3.2 Model Response to Reduction Scenarios

When emissions are reduced uniformly by 10 percent across the study area, InMap predicts 7.7% reduction in concentration, while AERMOD predicts a 10% change on average. The shape of the curves in Figure 4-5 indicates that there is a difference in which the models are predicting concentration changes. The AERMOD curve is indicative of the Gaussian plume dispersion formulas that inform the model; the change in concentration is a function of the cumulative change in the emissions of all sources which follow a normal distribution of dispersion and the variance in the change in concentration predicted in each grid cell will be a function of this distribution. For InMap, the change in concentration is limited as concentration increases, indicating that the InMap advection and deposition equations, which should dominate the prediction of Primary PM2.5 concentration, are limited as a function of concentration.

The change in concentration will be a function of the distance to peak emitters, which is demonstrated Figure 4-6 using three separate scenarios. In Figure 4-6a, the InMap predicted change in concentration is shown as a function of the distance to downtown Minneapolis (grid cell with peak on-road emissions) for a scenario in which onroad transportation emissions are reduced uniformly across the Minneapolis region. In Figure 4-6b and Figure 4-6c, the AERMOD predicted change in concentration is shown as a function of distance to the peak onroad and electricity generation emitters for scenarios in which an equivalent amount of emissions are reduced in the electricity and on-road transportation sectors. The similar shape of the curves in Figures 4-4a and 4-4b indicates that InMap and AERMOD are dominated by similar concentration prediction functions for ground-level sources such as transportation. The shape of Figure 4-6c shows that AERMOD concentration prediction for an elevated source, such as an electricity generation unit remains a function of distance, but that the maximum change in concentration will not be directly adjacent to the areas closest to the electricity generation unit. When running the same scenarios that generated Figures 4-6b and 4-6c using InMap, there was no distinguishable relationship between the distance to the source and the predicted change in concentration.

Figure 4-5 Percent Change in Primary PM2.5 Concentration due to uniform 10% Emission Reduction

a) AERMOD



b) InMap

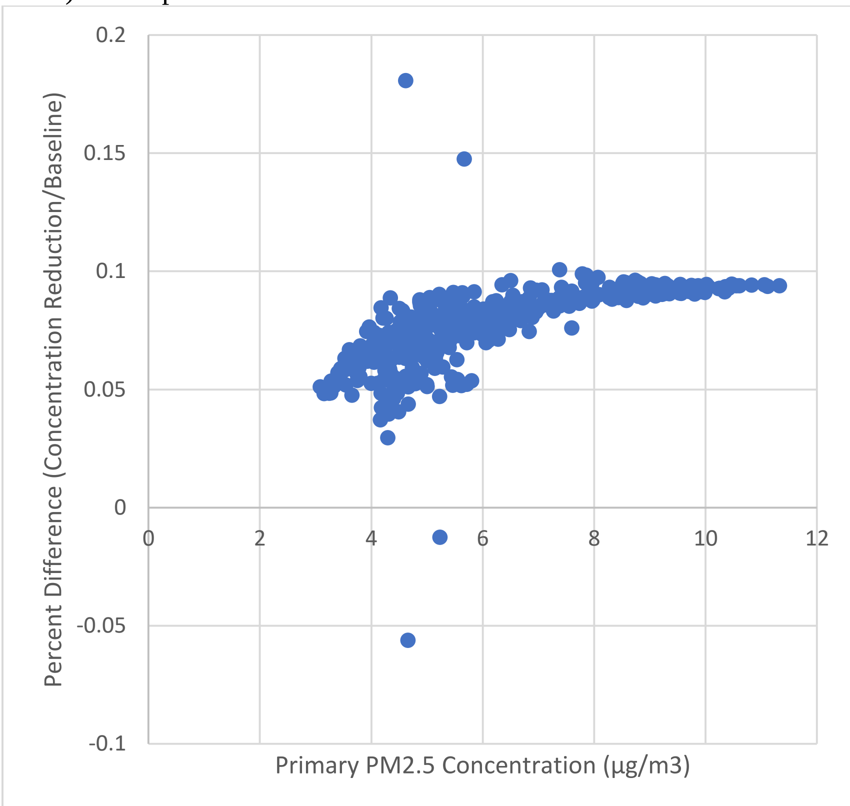
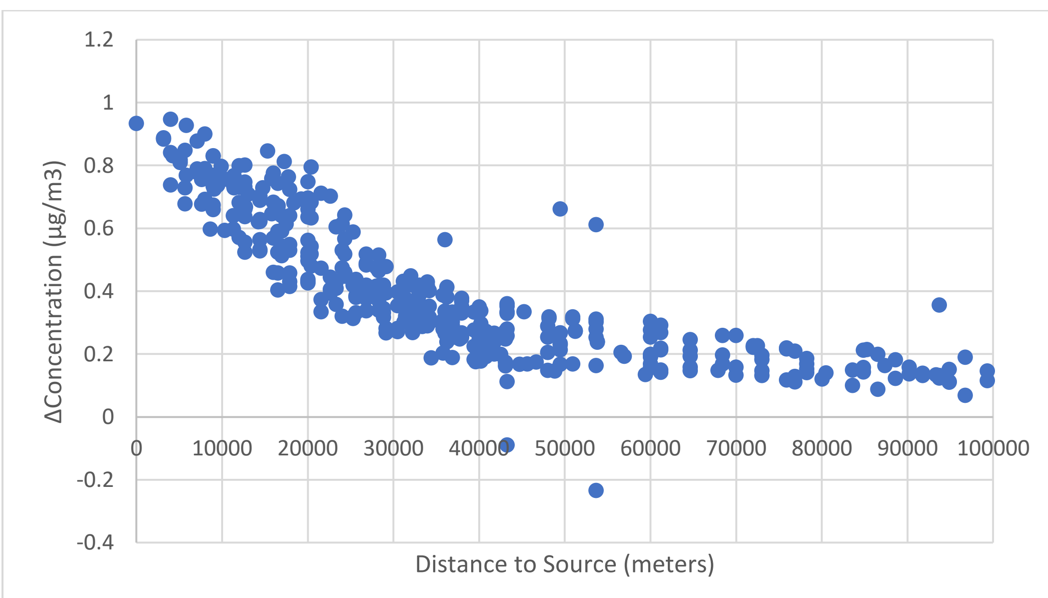
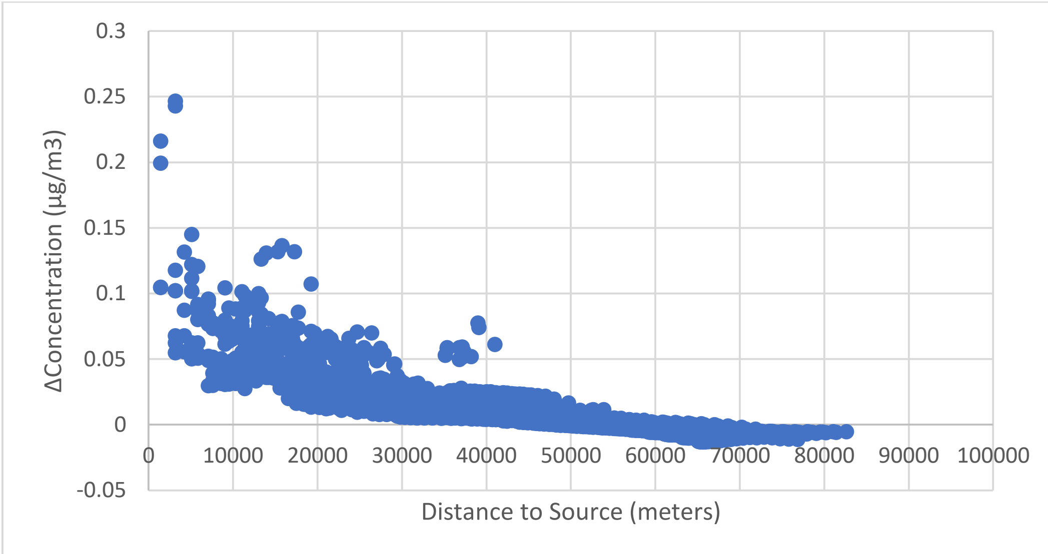


Figure 4-6 Modeled Change in Concentration as a function of distance to Peak Emitters

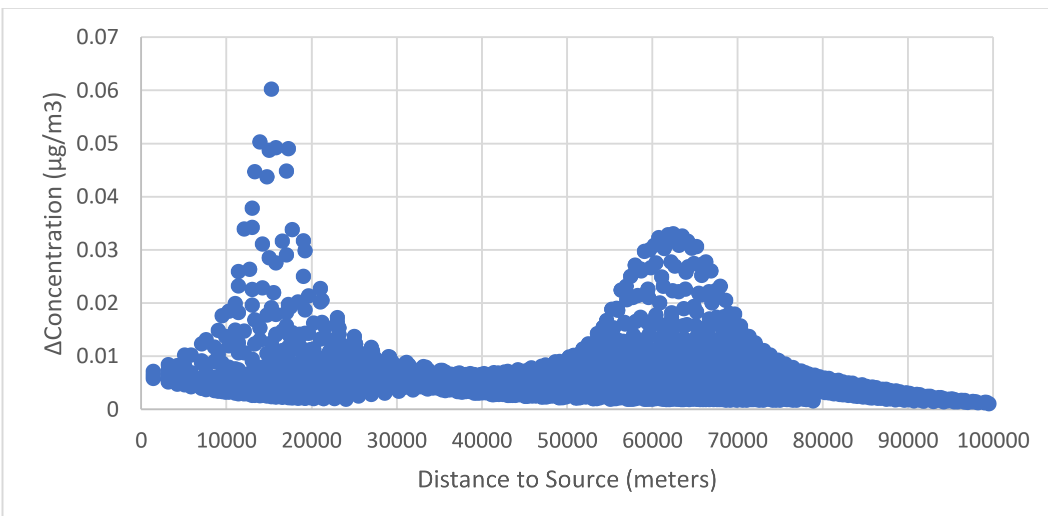
a) InMap Response to Uniform 10% Emission Reduction vs. Distance to Onroad Peak



b) AERMOD Response to 10% OnRoad Emission Reduction vs. Distance to Downtown MSP



c) AERMOD Response to EGU 100% Emission Reduction vs. Distance to Black Dog Power Plant



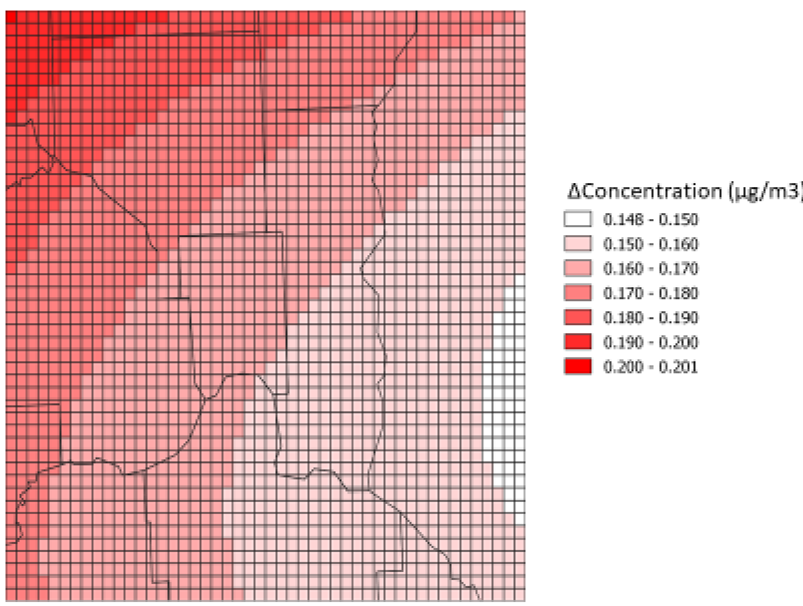
3.3 Estimated Impact of Primary-Secondary PM2.5 and Transboundary Pollution

The contribution of transboundary sources of pollution (from outside the Minneapolis metropolitan area) are quantified using scenarios in InMap and AERMOD. The results in Figure 4-7 show a distinct spatial relationship in the AERMOD prediction due to annual average wind rose direction and the distance from the distance from the city boundary. AERMOD predicts a 14% increase in primary PM2.5 concentration on average when including the emissions from the rest of the state. The magnitude of concentration increase is small, with the maximum change in concentration at 0.2 µg/m3 (indicated by the brightest red cells on the map). This makes sense given that AERMOD is recommended for predictions within 50km of the source.

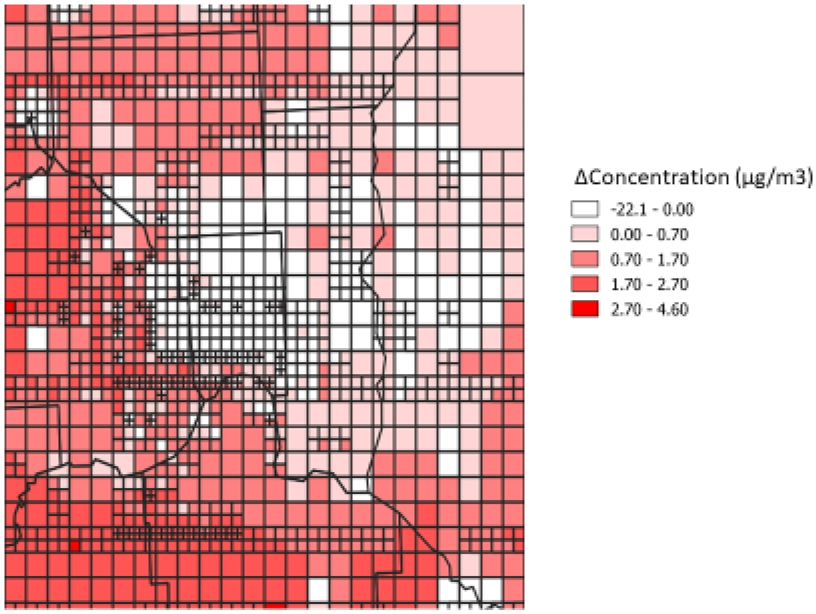
InMap predicts a similar concentration increase, on average, the primary PM2.5 grid cell concentration increases by 20% when adding emissions from outside the city. The maximum increase in concentration is 1 µg/m3 with 1/8 of the grid cells predicting a concentration decrease (likely due to smaller grid cell size in the scenario including only emissions from MSP). The secondary PM2.5 prediction in each grid cell increases by 26% when including pollution sources outside the city. On average across all 404 grid cells, the contribution of primary PM2.5 from sources outside the city is 0.2 µg/m3 while the contribution of secondary PM2.5 is 0.9 µg/m3.

Figure 4-7 Primary PM2.5 Concentration Change due to Transboundary Pollution Sources

a) AERMOD (Primary PM2.5 only)



b) InMap (Primary and Secondary PM2.5)



4. Discussion and Conclusions

The EPA has determined nationwide estimates of damages per ton PM2.5 in order to quantify the cost and benefits of reduced criteria air pollution through the Clean Air Act (USEPA 2011) and has explored sector-based variation in damages (Fann et al. 2012). Other models such as COBRA (USEPA 2018) and AP2 (Muller and Mendelsohn 2009) explore the county-level variations in direct damages from criteria air pollutants. Reduced complexity models (e.g. InMap, EASIUR, AP2) show similar trends in damages nationwide at the county level (Gilmore et al. 2019), but only InMap has explored the within county variation in marginal damages on average an 8-fold difference in the densest 10% of US counties (Goodkind et al. 2019). Here we show that for a metropolitan area on average, damages per ton PM2.5 are similar for AERMOD and InMap for ground-level sources but may vary 2-3 times in the case of elevated sources such as electricity generation units. Although damages per ton from onroad sources are similar (<10% difference) to sector-based nationwide estimates (Fann et al. 2012) for both models, they both are 2-5x less than Fann et al. (2012) estimates for electricity generating units. The damages per ton for both models are in line with Minnesota-specific estimates develop using EPA's BenMAP model (Kohlasch, Jackson, and Bael 2013; USEPA 2018)

The comparison of AERMOD and InMap shows that while there is general agreement in the baseline level of PM2.5 concentrations predicted by the models using the same emission inventory, the model architecture creates distinctions when emissions are reduced through scenarios. InMap and AERMOD both show distinct relationships with distance from source for ground-level sources such as on-road transportation, but only AERMOD shows a relationship for elevated sources such as power plants which is likely due to InMap treating elevated source emissions as being dominated by transport processes other than advection/dispersion. This also likely explains why AERMOD predicts are larger change in concentration to a uniform 10 percent reduction in emissions.

Since InMap and AERMOD are generally used to estimate changes in concentrations, not to more accurately match monitor air quality, it is necessary to understand the distinctions in the model response to assess the value in using these two models compared with other alternatives. Both AERMOD and InMap are dependent on the underlying emission inventory, which means that without high resolution inventory data it will be difficult to assess neighborhood level air pollution impacts using these models. InMap will show distinct spatial patterns with ground-level sources but may not be able to spatially resolve patterns in elevated sources dominated by mixing, reaction, and deposition equations. While AERMOD can estimate the spatial distribution of air pollution changes of individual sources, InMap is limited to spatial patterns resultant from changes in emissions at its inventory resolution determined by population density. For air quality and exposure assessments at the neighborhood level, this means that InMap can estimate changes in aggregate but likely cannot estimate changes in exposure due to individual emitters

Current tools (Bael et al. 2019; Ellickson et al. 2017) combined can achieve similar functionality but are not integrated; therefore while the regional implications of changes in emissions in individual emitters can be estimated, it is not possible to estimate the differential in neighborhood level exposure. InMap gets us closer to this capability, but likely only in aggregate, it cannot attribute the changes in air pollution concentration in one neighborhood to changes from an individual emitter.

Although the health benefits of reducing PM2.5 have been historically been quantified by various models due to their magnitude and implications for the net benefits of environmental policy, only recently have models become sophisticated enough to account for these benefits at a fine-spatial scale. This means that up until now, environmental policies which reduce air pollution have not had the scientific information necessary to take into account the distribution of benefits within counties. Scientific data has been limited by the spatial resolution of air pollution and transport models and by the limited distribution of air pollution monitors

New air pollution transport models such as InMap have been developed to address these issues, but they need to be compared to conventional models such as CMAQ and AERMOD used for regulatory purposes; similarly new low cost monitors are compared to conventional monitors to figure out how they need to be calibrated to supplement spatial estimation techniques of monitoring data (USEPA 2016). To address questions of air pollution equity and environmental justice, these new models must also be calibrated with existing models to understand how they complement current understanding at state level agencies. Critically, many of these new reduced complexity models are not built to provide regulatory guidance, but rather to estimate the marginal benefits of air pollution management alternatives. These models trade the computational time necessary for more accurate estimates of physical air pollution formation and transport for the ability to better estimate marginal benefits, the contribution of faraway pollution sources, and the spatial resolution necessary to within city/county variation.

Comparison of AERMOD and InMap allows us to determine the importance of secondary formation and the influence of external sources of pollution on baseline fine-scale exposure estimates. Experiments to look at uniform and non-uniform pollution reduction scenarios illustrate the lack of knowledge we have in attributing changes in neighborhood level air quality to pollution reductions from a particular source. As policies are introduced that limit carbon and air pollution from diverse emission sources (e.g. power plants, transportation, industry, residential heating), it is critical that policymakers have an understanding of the uncertainty and distribution of the resultant changes in air pollution exposure. Models with low computational complexity allow for the ability to analyze the bounded range of air pollution exposure under different scenarios, but they cannot guarantee that exposure will change in certain neighborhoods. Finer scale emission inventories and air quality monitoring data should be used to supplement the modeling results within communities with high pollution burdens in order to ensure that air quality is improving in front-line communities.

Chapter 5 - Bounding the co-benefits of carbon reductions in California: Aggregate and distributional impacts

Synopsis

California's policies to address greenhouse gas emissions are hailed as one of the most important sub-national steps to limit the effects of climate change. These flexible climate programs, which include a cap-and-trade program, a renewable energy portfolio standard, a zero-emission vehicle mandate, and a low-carbon fuel standard, are also seen as a critical mechanism to reduce local air pollution in California. Mitigating climate change and reducing local air pollution are generally seen as mutually reinforcing goals at the aggregate level, but this is not necessarily the case at the local level. Debate surrounding the extension and expansion of California's climate policies has drawn attention to the environmental justice argument that flexible market-based mechanisms do not guarantee reduced local air pollution emissions that may disproportionately affect low-income and minority communities. In other words, while flexible policies like cap-and-trade may cost-effectively achieve carbon emission reductions, they may not cost-effectively address local air pollution in all local communities.

Recent studies of California's cap-and-trade program have begun to address the intersection of climate policy and local air quality. These studies have focused on carbon and local air pollutant emission trends across communities in California. However, these studies have not explored the air quality and health implications for specific communities. In this paper, we study the distribution of air pollution co-benefits resulting from shifts in local pollutant emissions induced by California's climate policies.

We model the emissions behavior of more than 500 facilities regulated under Mandatory Greenhouse Gas Reporting Regulation, which account for approximately 80% of carbon emissions across the state. We develop bounded emission scenarios through 2030 to estimate the prospective criteria air pollutant emissions from these facilities under stylized policy regimes. By coupling this emissions data with a fine-resolution, reduced-complexity air pollution model, InMap, we assess how changes in criteria air pollutant emissions impact premature mortality due to chronic exposure to PM2.5 concentrations at the census-tract level. Our results allow us to quantify marginal health benefits from equivalent greenhouse gas reductions at different geographic scales and for different subpopulations. Differences in marginal health benefits illustrate the heterogeneity in localized impacts of carbon policies that reduce equivalent levels of greenhouse gases.

Given the uncertainties surrounding the magnitude and distribution of air pollution co-benefits of climate policies at the national level and in several other states, this work can inform the design of evidence-based policies to simultaneously address global climate change and local air quality.

1. Introduction

Climate and environmental policies affecting stationary sources of greenhouse gas (GHG) and criteria air pollutants are being designed to address multiple objectives: mitigating global climate change, improving air quality, and addressing disparities in environment-related health impacts. These policies span a range of regulatory approaches from command-and-control regulations to the flexible climate policies that don't guarantee emission reductions from a specific sector or source and are implemented in the context of federal environmental policies. The interactions between California's policies are complex, making impact assessment challenging. For example, there is rigorous debate concerning the distributional impacts of California's landmark cap-and-trade program in terms of health impacts in disadvantaged communities, spurring the adoption of complementary policies to specifically address air quality in the most polluted and poorest communities. As California continues to debate the appropriate mix of policies to address multiple objectives across multiple scales of impact, a particular analytic need has arisen to better characterize the impact of California's air and climate policies on the health of local communities.

The rationale for California's flexible climate policy is based on its flexibility to direct greenhouse gas (GHG) emission reduction efforts toward the opportunities that reduce emissions at lowest cost per ton. A focus on aggregate cost-effectiveness of climate policies is justifiable when a focus is placed on climate benefits alone because GHG emissions mix globally in the atmosphere and GHG emissions reductions have equivalent climate benefits regardless of where they occur. Yet many opportunities to reduce GHG emissions also reduce local air pollution (e.g. reducing coal combustion reduces carbon dioxide emissions and also reduces co-pollutants such as particulate matter, sulfur dioxide, and nitrogen oxide); the health benefits of this reduction in co-pollutants are generally referred to as co-benefits of climate policy. However, these co-pollutants do not mix globally and their reductions may have disparate health impacts on local communities. Climate policies create climate benefits that are universally shared due to the global mixing of greenhouse gases, but the health co-benefits of these policies will not be equally shared. Instead, the distribution of health co-benefits will likely be spatially heterogenous.

Differences in the local co-benefits of GHG reduction policies can arise due to (1) heterogeneity in the marginal cost of GHG emissions reductions that directs emissions reductions to specific locations, (2) heterogeneity in the rate of co-pollution of local criteria air pollutants with GHGs, and (3) historical inequities in exposure to local air pollution. Previous work showed differences in marginal benefits of emissions reductions for criteria air pollutants across the US at the county-level due to differences in population exposure (Muller and Mendelsohn 2009, 2012; Goodkind et al. 2019). Previous studies have also found inequities in risk exposure nationally and within cities across a variety of air pollutants (including NOx, PM, Ozone) (Saari, Thompson, and Selin 2017; Clark, Millet, and Marshall 2014; Fann et al. 2011; Goodkind et al. 2019). Together, these findings suggest that aggregate cost-effectiveness of climate policies may provide an incomplete assessment of benefits, as a significant share of aggregate benefits may not be globally shared; and therefore, a greater focus should be placed on the distribution of benefits that accrue to specific sub-populations and communities.

The factors driving differences in the local co-benefits of flexible climate policy described above imply that (1) a given climate policy can result in different levels of induced GHG emissions reductions, (2) a given level of GHG emission reductions can result in different levels of co-pollutant concentrations, and (3) a given level of co-pollutant concentrations can lead to different health impacts for sub-populations.

Taken together, the inherent flexibility of market-based GHG emission strategies are likely to lead to unequal local benefits to communities and could even raise the possibility of inducing net harms for specific areas (e.g. through the exacerbation of "pollution hotspots" in areas that have the highest GHG abatement costs). Potential differences in the local benefits of flexible climate policies have been a critical focus of policy and advocacy groups in the context of the well-established relationship between lower income levels and higher pollution levels. However, there remains limited evidence regarding whether, and to what extent, climate policies are strengthening or weakening this relationship.

Measuring the precise impact of pollution from any given point source on changes to health and the environment is challenging. Impacts are a function of a variety of variables, many of which are highly probabilistic or unknown. This along with uncertainty in the cost of pollution abatement makes it difficult to prospectively design policy to account for the local differentiation in benefits (Fowlie and Muller 2013). Critically, some have pointed out that variations in pollution exposure have yet to be quantified, but are necessary in order to understand the true distribution of the health co-benefits (Grainger and Ruangmas 2018). Therefore, this study seeks to improve the understanding of the distribution of local health benefits from California's recent market-based climate policies. Here we develop a first-order framework to determine how much these local benefits vary under stylized sectorally-focused scenarios that align with the policy goals of flexible climate policies in California such as the Low Carbon Fuel Standard, Sustainable Communities Strategy, renewables portfolio standard, and cap-and-trade reductions through 2030. Using a fine-scaled air pollution model, we are able to estimate the distribution of changes in air pollution exposure under these scenarios in specific regions differentiated by demographic characteristics such as whether the community is designated as “disadvantaged” by CalEnviroScreen.

1.1 Research Setting

As subnational governments implement climate policy both in support of and in the absence of national policies, market-based climate policies are seen as an environmentally effective and cost-minimizing solution for reducing GHG emissions. However, flexible climate policies are not enacted in isolation; various other binding climate, energy, and air quality policies may have been implemented prior or concurrently. Any cost-benefit analysis should condition on these existing policies, but policies are enacted and revised progressively making quantification difficult. In California, climate and air quality policies are being implemented in tandem, with the Air Resources Board broadly having jurisdiction over carbon and air pollution targets. Many of the same point source polluters are being regulated by the policies concurrently, making quantification of the emissions reduction benefits difficult to attribute to a specific policy.

California climate and air pollution policies (negotiated in the 2017 AB 398 extension and Scoping Plan) have been developed concurrently with the cap-and-trade program to develop sectoral pathways to reach statewide carbon targets by 2030. Ideally, this would result in carbon emission reductions at lowest cost, however the market design of the cap-and-trade program does not take into account the localized nature of binding policies administered regionally (e.g. Sustainable Communities Strategy, Permitting by the Air Quality Management Districts).

Previous work has illustrated the potential drawbacks of binding, complimentary environmental policy (Goulder and Stavins 2011) nested within a larger scale carbon market. Depending on whether the binding policies are more or less stringent and whether the sectoral coverage overlaps, the binding policy could either induce the same amount of emissions at higher cost or it may not have any effect (Stavins and Goulder 2012)

If we view California's cap and trade program and its complimentary policies (LCFS, SCS, RPS, etc.) through this lens, then the question becomes less about whether flexible climate policy is an effective backstop to ensure carbon emission reductions and more about whether the interactions between the policies result in the optimal level of emissions being reduced at the lowest cost. California's program design ensures that if costs are not minimized, then the free allocation coupled with consignment auction (Busch et al 2018) will prevent costs from rising rapidly. California's climate policy scoping plan alongside the cap and trade market then ensures that the state maintains a trajectory of emission reductions that will enable an 80% reduction in GHG emissions by 2050 (CARB 2017)

Critically, the design of these policies does not seek to maximize social welfare or optimize the benefits of the various climate policies. Rather the goal of these policies is to reduce carbon emissions to a given level within a certain price range. Given the uncertainty over the marginal abatement costs of individual polluters and industries, it is unclear which polluters will choose to reduce their emissions and by what amount. Instead, this paper explores the marginal benefits that may be induced by climate policy.

In investigating which policies are advantageous for social welfare, it is important to accurately assess the benefits of reducing co-pollutants when assessing the impacts of binding and market-based climate policy. It is also critical to assess the spatial distribution of these benefits because they tend to have heterogeneous spatial dispersion patterns, unlike carbon which globally mixes in the atmosphere. Therefore, the marginal benefits of reducing co-pollutant emissions will vary across space, sector, and potentially over time (e.g. seasonality of power plant emissions). This work seeks to provide evidence about this variability in marginal benefits, with a focus on disadvantaged communities

Addressing the impact of reducing PM2.5 emissions is critical for air pollution and climate policy moving forward, as the state seeks to reduce carbon emissions by 40% by 2030 while also reducing pollution burdens in front-line communities. To assess the impact on front-line communities, climate policy and air pollution management plans both need to assess the cumulative impacts of variation in pollution sources on disadvantaged communities. While monitoring networks assess changes in air quality over time and across policy regimes, they are limited in their ability to prospectively assess potential pollution reductions and they need to be connected to emissions data in order to assign pollution reduction benefits in multiple communities across multiple policy regimes. Without prospective analysis of these marginal benefits, climate policies with the potential to reduce local pollution burdens will only be able to be assessed retrospectively using local monitored air quality measures.

By developing scenarios based on the sectoral targets of emission reductions in California and applying these emission reductions to an air pollution model to simulate future air pollution exposures under different policy regimes, this exercise will be particularly useful for discussions of whether the benefits of market-based environmental policy are distributed equally and whether climate policies being considered through 2030 could achieve greater health benefits if supplemented with more sectorally- or locationally-specific command and control policy

1.2 Policy Background: Flexible Climate Policies

California state government has put forth significant resources to create flexible climate policies under the 2017 Climate Change Scoping Plan (including cap and trade, renewable portfolio standards, low carbon fuel standard, EV mandates, etc.) that reduces carbon emissions but does not reduce the state’s economic competitiveness. The overlapping policies seek to reduce carbon emissions by 40% by 2030 while minimizing the marginal abatement costs of regulated entities (CARB 2017). The cap-and-trade extension (AB398), which extends the current system from 2021-2030, met significant resistance from environmental groups who argued that the current flexible climate policies did not go far enough in ensuring that emissions within California would decrease and reducing pollution burdens in front-line communities.

1. 2017 Scoping Plan (including Cap and Trade)

California passed the re-adoption of its cap-and-trade program (AB 398) extending a key component of its efforts to reduce GHG emissions by 2030. Emissions regulated by the 2017 Scoping Plan (CARB 2017) are considered “covered sector emissions” and account for roughly 80 percent of all greenhouse gas emissions reported in the state of California. These sectors include point-source pollutants such as large industrial facilities, electricity generation, transportation, and residential and commercial consumers (CARB). Critically, the Scoping Plan does not set any mandatory emissions reduction targets for any particular sector (e.g. oil refineries), although this was considered in the agencies plans prior to the passage of AB 398 (CARB 2017b). Due to the flexibility built into the cap-and-trade market, Renewable Portfolio Standards, Short Live Climate Pollutants, Low Carbon Fuel Standard, and other policies set targets for transitioning away from fossil fuels in the energy (electricity and transportation fuels) sector. Air quality management districts (AQMDs) will continue to regulate regional air quality through programs limiting criteria air pollutant emissions but will no longer have any jurisdiction over GHG emissions reductions. Critics of the current iteration of the cap-and-trade program, generally, point to two specific issues; an oversupply in the allocation of allowances and offsets that will artificially keep carbon prices low removing incentives for covered sectors to invest reducing their emissions.

2. Sectoral Policies (Transportation/Electricity/Refineries)

The transportation sector is largest source of carbon emissions in the state and there are various policies in place to reduce vehicle activity and adopt low-carbon fuels. The California Low-Carbon Fuel Standard (LCFS) is anticipated to drive emissions reductions throughout the transportation sector by setting a target on the carbon intensity (g CO2/MJ) of the in-state fuel market. Unlike the statewide cap-and-trade program, the LCFS has not placed a cap on overall sector emissions or set a volume quota on petroleum production, but rather constitutes a primarily supply-side intervention by facilitating a switch in production of alternative, less carbon-intensive fuels (e.g. biofuels, electric, natural gas, hydrogen) in place of conventional gasoline and diesel usage. The LCFS program works concurrently with the Sustainable Communities Strategy which sets targets for reduced vehicle miles traveled (VMTs) at the community level and the ZEV mandate which has set a target of 1 million Zero Emission Vehicles (ZEVs) sold by 2025. These policies together will reduce demand for refined products in California. These changes in in-state demand for gasoline and diesel may induce refineries to invest in efficiency upgrades to reduce costs and emissions, carbon capture and sequestration (CCS) technologies depending on LCFS credit value, or capital investments to export their products. LCFS has faced numerous legal challenges which have led to a steady carbon intensity target since 2015. In the Fall of 2018, the LCFS program was extended to reduce the carbon intensity of transportation fuels by 20% through 2030. The initial program design and the slower than expected ramp up of carbon intensity targets has led to a surplus of credits, mainly generated by biofuel producers (Witcover et al. 2018). As carbon intensity targets become more stringent, the expectation is that zero emission vehicles powered by electricity, natural gas, or hydrogen will take over the bulk of LCFS credit generation. However, if these new technologies are not adopted quickly enough, then a shortage of LCFS credits may force refineries to either cut production, export refined products, or further reduce emissions.

Electricity producers (EGUs) and fuel producers (refineries) are also impacted by LCFS in that they can buy and sell credits in the market depending on the carbon intensity of the transportation fuels being sold. However, other policies will likely drive the behavior of the facilities, such as renewable portfolio standards, short-lived climate pollutants, and refinery investment credits.

3. Scenario Development Under Flexible Climate Policies

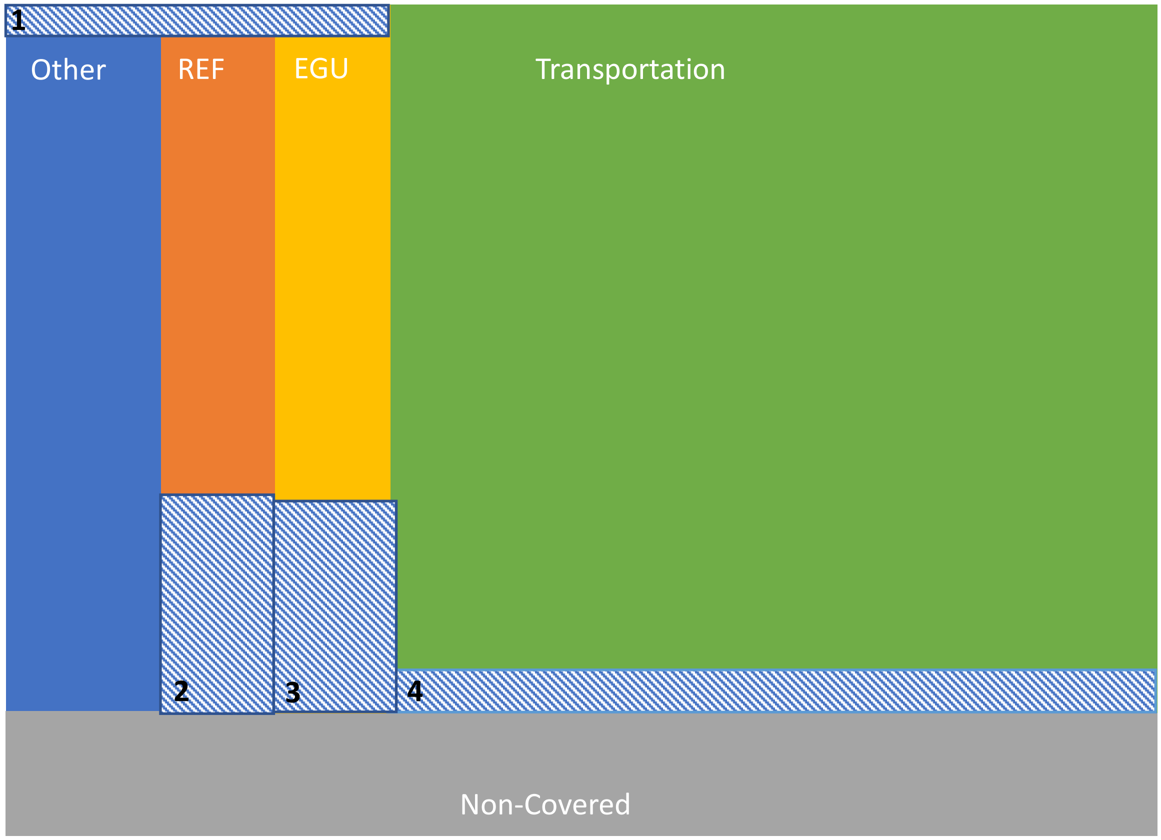
Given the flexible nature of California's climate policy, four stylized scenarios are created to simulate equivalent statewide CO2 reductions that could occur under climate policies. These scenarios illustrate how equivalent CO2 emission reductions could have variable aggregate health benefits depending on the sector reducing emissions.

The treemap in Figure 5-1, illustrates the carbon emissions reduced in each scenario broken down by sector. Covered Sector emissions (including covered sector facilities, transportation, and imported electricity) in California represent approximately 80% of statewide CO2 emissions. Covered Sector Facilities represent ~100 MMT CO2 with electricity generation and refineries each representing about ~30% of this total, while onroad transportation emissions are approximately 1.5x the covered sector facilities. A 10% reduction in statewide emissions from covered sector facilities is equivalent to 10 MMT CO2 reduced in aggregate, represented by Scenario 1. An equivalent amount of emissions is reduced proportionally in the electricity, refinery, and transportation sectors to generate scenarios 2, 3, and 4. Criteria air pollutant emissions are reduced by the same percentage as CO2 reductions in each sector. The equivalent emission reductions in each sector are then broken down into increments representing 2.5% of statewide covered sector facility emissions to generate 35 different combinations of potential emission reductions.

Table 5-1 Stylized Emission Reduction Scenarios and Policy Targets

SCENARIO	SECTOR	RELEVANT CLIMATE POLICIES	10% STATEWIDE EMISSION REDUCTION TARGET	UPPER BOUND OF POLICY TARGET
1	Covered Sector Facilities (CS)	Cap and Trade Program, Short Lived Climate Pollutants Reduction Strategy	10% CO2 Reduction in Covered Facilities	40% by 2030
2	Refineries (REF)	Low Carbon Fuel Standard, Cap and Trade Program	32% CO2 Reduction in Oil Refineries	30% by 2030 under LCFS low demand scenario
3	Electricity Generation (EGU)	Renewable Portfolio Standards, SB100, Cap and Trade Program	31% CO2 Reduction in Power Plants	60% renewables by 2030, 100% by 2045
4	Transportation (TRANS)	Zero Emission Vehicle Mandate, Sustainable Communities Strategy, Low Carbon Fuel Standard	6% CO2 Reduction in OnRoad Vehicles	19% reduction by 2035

Figure 5-1 Conceptual Diagram of Emission Reduction Scenarios Compared to Statewide Sectoral Emissions



1.3 Literature Review

Estimating health benefits of environmental policies at high spatial resolution is difficult. In particular, uncertainties surrounding the dose-response function have led to various estimates of relative risk of human exposure to PM2.5 (Burnett et al. 2018). Efforts to compare the uncertainty in the dose-response function to variations in population, emissions, climate, and other variables require sophisticated IAMs (Saari et al. 2019). However, we do know that PM2.5 causes more than 3.2 million premature mortalities globally concentrated in highly populous countries and that policies to reduce exposure even in relatively clean counties could have significant health benefits due to the shape of the dose-response curve (Apte et al. 2015). There exist significant variations in within county PM2.5 concentrations that are likely due to variability in primary PM2.5

emission sources (Gu et al. 2018; Shah et al. 2018; Ye et al. 2018) – indicating that changes in emissions in highly polluted areas of CA may yield high marginal health benefits.

Despite the difficulty of estimating health benefits at a high spatial resolution, there is evidence in the US and globally that the health co-benefits of climate policies may be of comparable value and could even both outweigh these policies' direct costs (suggesting that climate policies create net benefits even ignoring their cost) and could outweigh their carbon benefits (suggesting the importance to considering health co-benefits as a high priority in designing climate policy). Globally, the health co-benefits of reducing GHG emissions to meet the Paris Climate Agreement targets of 1.5-2°C have been shown to be greater than the direct costs of reducing GHG emissions, even after accounting for uncertainty in valuation of premature mortality benefits (Markandya et al. 2018). In the US, previous studies at the national level have modeled the ancillary health benefits of low-carbon policies, such as cap-and-trade (Thompson et al. 2014) and the Clean Power Plan (Fowlie 2018), showing that the health benefits of reducing co-pollutants, such as PM2.5 and ozone, outweigh these policies' direct costs. Other regional US studies, looking at the air pollution co-benefits of carbon policy in the Northeastern US (Thompson et al. 2016) and California (Zapata, Muller, and Kleeman 2013), have shown that regional health co-benefits could by themselves exceed the costs of cap-and-trade, depending on the variability of the regional energy portfolio and the potential criteria pollutant co-benefits from the adoption of GHG emission controls.

Flexible policies, by their design, do not guarantee similar ancillary benefits across space. Therefore, flexible policies may place a disproportionate health burden in specific communities, including those that have historically faced higher levels of air pollution. However, the empirical literature surrounding this question has come to mixed conclusions. Recent studies focusing on California have used two market-based programs (RECLAIM and AB32) to estimate whether there is systematic variation in the emissions reductions of industrial polluters and electricity generation units across different communities, finding no significant difference across communities based on race or income (Fowlie, Holland, and Mansur 2012; Walch 2018). Further study of the RECLAIM program, which set market-based limits on criteria pollutant emissions from point sources across an air basin, found that larger emission reductions occurred in higher income communities when controlling for race and found larger reductions in black communities compared to Hispanic communities when controlling for income (Grainger and Ruangmas 2018). Similarly, a national study of the federal Clean Air Interstate Rule found higher emission reductions in high-income, non-minority communities. Older, dirtier plants are likely to be located in low-income, minority communities which will likely either have to shutdown or be too expensive to retrofit with current control equipment leading utilities to abate pollution at facilities where it is cheaper to retrofit (Andaloussi and Isaksen 2017).

Recent debate within California has focused on the proximity of high emitting facilities to low-income and minority communities and changes in emissions of these facilities since cap-and-trade enforcement began in 2012 (Cushing et al. 2018; Meng 2017). Various academic studies have sought to determine if cap-and-trade alleviates these burdens but have not come to a consensus regarding whether cap-and-trade is reducing GHG emissions faster in disadvantaged communities (Meng 2018) or whether these communities see little to no emission reduction (Cushing et al. 2018; Pastor et al. 2010). The relationship between cap-and-trade and local air pollution is further obscured by the fact that GHG-to-co-pollutant emissions ratios vary by industry and facility type (OEHHA 2017). None have determined the health implications of these changes in emissions, while others have pointed out the uncertainty in whether reductions in carbon emissions will have any impact on co-pollutant emissions (Anderson et al. 2018). Our study moves beyond this debate to estimate how equivalent reductions in statewide carbon emissions could have variable health benefits in specific communities across California depending on which sectoral climate policies are binding. We demonstrate that aggregate benefits of sectoral climate policies could have varied localized impacts on communities, implying that the distribution of these health benefits will not be equivalent across communities.

2. Methods

To determine the impact on local communities of prospective climate policies in California, air pollution transport models with the ability to estimate high spatial-resolution changes in air quality must be utilized to connect changes in emission to changes in exposure.

2.1 Approach

By assessing the variation of air pollution costs and benefits under flexible climate policy, this work will contribute to the literature on the distributional effects of climate change policies across local communities and subpopulations and could help inform the design and implementation of complementary air pollution policies focused on reducing disparities. Similar to prior evaluations (OEHHA 2017), our study will not address the investment of cap-and-trade revenue in disadvantaged communities. Given the multiple air and climate policies regulating facilities simultaneously, we develop policy-relevant scenarios to project facility-level emissions through 2030. These scenarios are then utilized by an air pollution model to measure the heterogeneous changes in air pollution exposure across California resulting from these emissions reductions.

Not all of California's climate and air quality policies have binding targets, so facilities may choose to reduce emissions to comply with existing air quality regulations and buy permits to comply with market-based policies depending on each facility's marginal abatement cost. Therefore, there is uncertainty in the actual emission reductions that will be induced by market-based policies. Because facility-level cost estimates were unavailable and the marginal abatement costs of each policy are difficult to determine given the uncertain amount of emissions being reduced by each policy, we chose the approach of estimating an upper and lower bound of emissions reductions induced by different policies.

For each of the 500+ point source facilities that must comply with flexible climate policies under the 2017 Scoping Plan, emission reductions in 2030 are estimated across refinery, onroad transportation, electricity generation, and other covered sector sources. Climate and air pollution policies are assumed to uniformly reduce emissions across industries due to the uncertainty in the magnitude and facility location of future reductions. Therefore, the scenarios illustrate the potential statewide impact of emissions reductions induced by current climate policies. The location and physical characteristics of these reductions are assigned based upon the 2014 National Emissions Inventory and source classification codes (USEPA), meaning that marginal benefits estimated by the prospective policy scenarios are independent of facility-level marginal abatement costs and variations in local air quality regulations at the air quality management districts.

The initial prospective analysis consisted of 25 scenarios that bound the range of expected emission reductions as facilities respond to statewide reduction targets of up to 40% by 2030. Figure 4-2 demonstrates the marginal benefits in one community as a function of the emission reduction scenarios ranging from 10-40% across refineries and covered sector facilities regulated under the cap-and-trade program.

2.2 Sectoral Scenarios

Scenarios are developed to simulate the range of reductions that could occur under the current scope of California climate policies. Certain policies may have binding targets on specific sectors (e.g. electricity and transportation) while other policies (e.g. Cap and Trade) may have statewide targets, but lack definition in the sectors or locations where reductions must occur. We utilize the source classification codes from the 2014 National Emissions Inventory to assign 10% emission reductions uniformly across transportation, electricity generation, refinery and cap-and-trade covered sectors. Electricity generation and refineries make up more than 55% of carbon emissions from statewide facilities covered under the Mandatory Reporting of Greenhouse Gas

Emissions Regulation and more than 75% of emissions in LA County. Transportation (onroad) and covered sector facilities make up approximately 85% of statewide carbon emissions and many of these sources are of highlighted in addressing air quality concerns of environmental justice advocates. Table 4-1 details the characteristics of the emission scenarios and the InMap model specifications used for scenario analysis.

Utilizing the 10% reduction scenarios across these four sectors, we explore the marginal benefits of equivalent emission reductions across multiple scales. Three of the four sectors impact elevated emission sources, while the inclusion of the transportation sector allows us to explore the impact of ground level marginal benefits compared to high stack height sources in aggregate. By investigating the marginal benefits of emission reductions across LA County, Disadvantaged Communities, and one specific DA community (Wilmington) we show whether certain policies have different marginal benefits in disadvantaged and non-disadvantaged communities.

We then run 35 scenarios with the same 10% reduction in emissions distributed across the four sectors in 2.5% increments. This is intended to simulate the fact that none of these policies exist in isolation, but certain policies may have a more pronounced effect on specific communities. For example, policies targeting refinery emission reductions could have large benefits in Wilmington and Los Angeles but limited effects in San Francisco. By examining all combinations of emission reductions in the four sectors, we can examine the range of marginal benefits within a given community to determine whether a sectorally-specific strategy (e.g. permitting, command and control) or suite of strategies will have more marginal benefits. The shape of these marginal benefits curves also indicates whether sector-specific strategies or a combination of strategies maximize marginal benefits in a given community.

Lastly, we investigate the aggregate benefits of each policy across all census tracts in Los Angeles. While certain policies will have pronounced effects in nearby communities, the implications of these pollution reductions may be beneficial for many communities regionally.

However, the distribution of these benefits may vary depending on the location and physical characteristics of the source. By creating histograms of the difference in benefits of each of the four policies, we can examine whether certain policies maximize local benefits only in certain communities or whether these benefits are distributed across disadvantaged communities. For example, the air pollution implications of reducing transportation emissions may be felt across all urban areas in California, but the marginal benefits could be higher in communities located nearby freeways.

2.3 Air Pollution Modeling

Previous models (e.g. AP2, InMap) have identified heterogeneity in emissions reduction at the national and subnational level (Dimanchev et al. 2018; Muller, Mendelsohn, and Nordhaus 2011) and questions about the differences in long-term exposure to air pollution in underrepresented groups (Di et al. 2016, 2017), which has led to questions about the effectiveness of national air quality markets (Andaloussi and Isaksen 2017). Previous models in California have run prospective scenarios of emissions under climate policy scenarios but have been unable to differentiate between the heterogeneous benefits of reducing emissions at different sources (Zapata et al. 2018). While other deterministic models in California have examined the sources of pollution that need to be regulated in order to achieve better air quality, these models are not well-suited for studying policy co-benefits due to their spatial resolution and high computing requirements. Regulatory models (Office of Community Air Protection 2018) are limited by computing power, technical requirements, and spatial resolution in the case of photochemical models (e.g. CMAQ, CAMx) and while fine-scale dispersion models (e.g. Calpuff, AERMOD, HARP) can estimate air pollution levels close to high emission sources, these models do not take into account secondary formation of PM2.5 due to precursors such as SOx, NOx, and VOCs. In order to answer questions related to environmental justice implications of emission reduction policies, it is critical that air pollution models have sufficient resolution to differentiate between pollution exposure across neighborhoods and demographic groups (Nguyen and Marshall 2018; Paolella et al. 2018).

Previous California studies have identified the need for high spatial resolution (less than 4x4km) in prospective air quality models used to estimate the heterogeneous air quality impacts of climate policy. Previous work optimizing least cost pathways for 80% GHG reduction in California's energy sector shows 14% decrease in concentrations in SCAQMD (Zapata et al. 2018). Although multiple models have been developed to estimate pathways for clean energy and climate policy, there remains need for a model that assesses the heterogeneity in impacts of climate/clean energy policy across sectors and income groups (Yeh et al. 2016). Therefore, in this study we implement a reduced form air pollution transport model with high spatial resolution to better characterize the relationship between pollution sources and local air quality (rather than relying on simple geographic distance between sources and populations)

This study takes advantage of new air quality models that can be used to estimate air pollution levels at high spatial resolution with limited computational intensity. In order to answer questions about environmental justice and heterogeneity of impacts across socioeconomic groups, it is imperative to have an air pollution model that estimates within county variation, while also capturing the impacts of secondary formation on communities that may not be located in close proximity to the pollution source. Most studies have used dispersion models to estimate concentrations at high spatial resolution or chemical transport models to determine both primary and secondary formation of air pollution, but these chemical transport models are unable to be used for scenario analysis due to their computational intensity.

New Air Pollution Models (InMap)

Previous CTM models (e.g. CA-REMARQUE) are too computationally intensive to be run at the spatial resolution necessary to determine differences in pollution in disadvantaged communities at the census tract level, while current models analyzing pollution hotspots (HARP) may only capture primary air pollution levels but are unable to account for secondary formation. Recently, reduced form tools (i.e. InMap, AP2, EASIUR) have been developed as less computational alternatives with InMap specifically being utilized to inform environmental justice issues whereas coarse-resolution models may underestimate exposure disparities among minority and low-income populations (Tessum, Hill, and Marshall 2017; Paolella et al. 2018). The high spatial resolution of the model in urban areas (up to 1x1 km) allows the model to capture within county differences in pollution exposure resulting from marginal changes in emissions across demographic groups (environmental justice) or neighborhoods. These estimates are overlaid upon county-level mortality rates and population data at the census tract level to determine premature mortality rates using the GEMM exposure response function. Premature mortality rates resulting from air pollution exposure across subgroups are calculated based on the population-weighted average of exposure providing a quantitative measure of the disparity in health benefits.

InMap (Tessum, Hill, and Marshall 2017) simulates changes in air quality and premature mortality at the sub-county scale (up to 1x1 km) with limited computational intensity. This allows us to run multiple scenarios to estimate premature mortality changes under different policy regimes. Facility-level estimates of criteria air pollutant emissions (NOx, NH3, SOx, PM2.5) are input into the model to estimate primary and secondary formation of PM2.5. It is critical to use a model that accounts for secondary formation of PM2.5 and models concentrations at the sub-county scale, in order to estimate changes in air quality in disadvantaged communities that may suffer from indirect formation of PM2.5 and not be located within 2.5 miles of facilities (the distance used by Cushing et al. 2018).

InMap produces concentration exposure estimates at up to 1x1km grid scale. This is critical because health impacts per unit of emissions of PM2.5 and its precursors vary across locations (N. Z. Muller and Mendelsohn 2009; Tessum et al. 2019; Tessum, Hill, and Marshall 2017).

Therefore, such a fine-scale of spatial resolution is needed particularly when quantifying differences in exposure among demographic groups (or disadvantaged communities).

2.4 Data

Emissions Data is derived from the 2014 National Emissions Inventory (US Environmental Protection Agency 2016) and compared to data from the California Air Resources Board MRR facilities. Publicly available emissions data from 2008-2015 is available for criteria air pollutant and GHG emissions from the CEIDARS and MRR databases. Although air pollution and carbon emissions are connected via the Air Pollution Mapping Tool (ARB), data for criteria air pollutant emissions (including stack height and other physical characteristics) are identified based upon individual stacks, while carbon emissions are calculated at the facility level. Given the changing subset of facilities that have been required to report carbon emissions, under the MRR program, we use SCC codes for all point source facilities in the NEI 2014 database, to compare prospective scenarios of GHG reduction to the potential reductions in criteria air pollution emissions.

Using similar emission datasets of carbon and criteria air pollutants used by previous studies (Anderson et al. 2018, Cushing et al. 2018) this study prospectively assesses how these facility-level changes in emissions will occur based on the binding and non-binding regulations in place through 2030. Emission reductions are distributed to facilities based upon their source classification codes, simulating a uniform reduction of criteria air pollutants across industries. The air pollution model then simulates expected air pollution concentrations based on 2014 emission levels compared to prospective scenario emission levels. These concentrations are assigned to each grid cell and then used to estimate the exposure of the population within that same grid cell. Population by age and race is assigned from each census tract/block from the IPUMS NHGIS (Manson et al. 2018) dataset. Mortality rates at the county-level are used to estimate baseline health risks of the overall population. The GEMM dose-response function converts changes in air pollution levels to elevated risk of NCD and LRI diseases, which are then applied to these population and baseline mortality estimates.

2.5 Health Benefits

The GEMM dose-response function allows us to model the changes in premature mortality due to air pollution at levels above 2.5 micrograms/m3. Using the prospective bounded emission scenario approach described above, we can estimate changes in premature mortality benefits at the county and census tract level due to changes in facility emissions under flexible climate policies. Premature mortality is attributed to each grid cell based on population-weighted PM2.5 concentrations. County-level benefits are calculated based on the aggregate population in each county exposed to the population-weighted PM2.5 levels.

Census-tract-level air pollution-related mortality rates are assigned based on the area-weighted average of grid cells covering each census tract. Benefit ratio of LCFS is determined based on two scenarios (1) 31% refinery reduction and (2) 10% covered sector facility reduction which have similar statewide CO2 emissions reductions. The ratio is calculated as the change in mortality under the refinery scenario and covered sector scenario compared to the base case, where census tracts with a ratio>1 have greater benefits from refinery reductions. Difference in mortality rates across the two scenarios is also calculated based upon the premature mortalities avoided and the total population in each census tract.

Premature mortality and population-weighted concentration are estimated across Disadvantaged Communities, Non-Disadvantaged Communities, and Wilmington (given its proximity to the Port of LA and refineries). Premature mortality due to noncommunicable diseases (NCDs) and lower respiratory infections (LRIs) is estimated using the GEMM exposure-response function (Burnett et al. 2018) for PM2.5 concentrations above 2.4 µg/m3 and all-cause mortality estimates ("CDC WONDER Online Database" 2014). Grid cells within LA County are selected using IPUMS population data at the census tract level to develop estimates of population-weighted exposure.

Using the gridded estimates (1-48km gride cells) of PM2.5 concentrations and premature mortality estimated by InMap, exposure and health benefits are aggregated at the county, air basin/district, and census tract scales. The main unit analysis of marginal health benefits occurs at the census tract level, so that changes in air pollution exposure can be correlated demographic data and the disadvantaged community designation. Air pollution exposure measured by InMap is converted into premature mortality rates for each grid cell using the GEMM exposure response function. Mortality rates are then aggregated at the county and air basin level to determine the shape of the marginal benefits curve across different locations in California. At the census tract scale, mortality rates are assigned based upon an area weighted average in order to compare changes in exposure across disadvantaged and non-disadvantaged communities and across socio-demographic groups.

2.6 Spatial Analysis of InMap Results

InMap's variable resolution grid allows for prediction of changes in air quality and exposure at up to 1x1km resolution. This is important for assigning changes in exposure to a consistent spatial unit of analysis at the census tract level.

Marginal Benefits of sectoral scenario reductions equivalent to 10% statewide CO2 emissions are determined based on the change in premature mortality due to PM2.5 exposure in each census tract. Each scenario has a predicted amount of premature mortalities in each grid cell (up to 1x1km). An area-weighted average of PM2.5 concentration is assigned to each census tract based on the percentage overlap between each grid cell and each tract. The change in air pollution exposure is then calculated as the change in air pollution-related mortality rates in each census tract based on the GEMM exposure-response function. The change in mortality rates for each census tract are then aggregated for LA County, Disadvantaged Communities, and Wilmington based upon the population weighted change in air pollution related premature mortality per

100,000 people. Census tracts lacking population data or with average concentrations below 2.4 μg/m3 in the base case are assumed to have zero air pollution-related premature mortalities and removed from the sample.

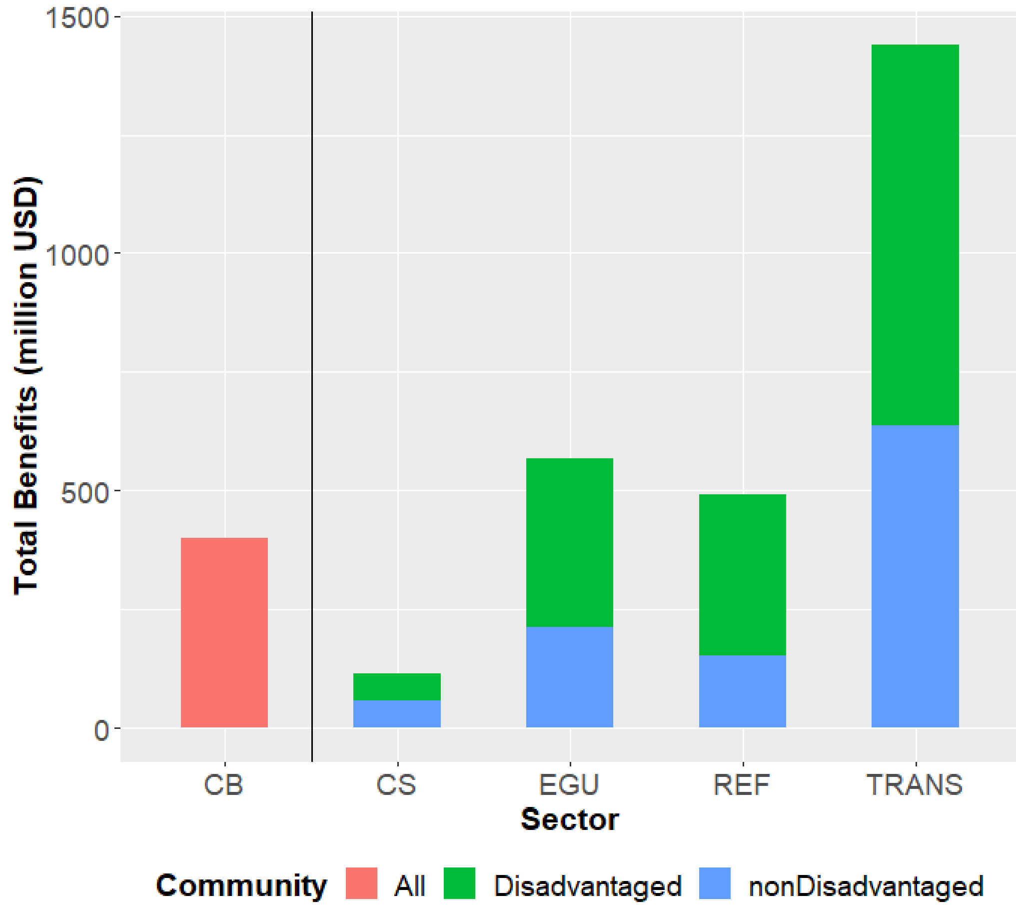
These marginal benefits are calculated for 35 different scenarios representing the possible combinations of sectoral emission reductions that could occur to achieve a 10% statewide CO_2 emission reduction. The range of marginal benefits is then calculated for varying levels of reduction in each sector to demonstrate which set of policies are preferred by different spatial aggregations.

The distribution of benefits across census tracts is also calculated for each of the four sectoral reductions to determine if certain policies distribute benefits more uniformly across all communities. We overlay the disadvantaged communities' designation to determine how different the health benefits induced by these policy changes will be spatially. Disadvantaged communities are designated based upon the top 25% of communities scoring based upon environmental exposure, sensitivity, and socioeconomic characteristics (OEHHA 2017). By looking at the distribution of health benefits across disadvantaged and non-disadvantaged communities in Figure 5, we can determine whether there is a difference in the spatial distribution of health impacts between different climate policies.

3. Results

Across the four scenarios illustrated in Figure 5-1, statewide carbon benefits (CB) are the same at ~$310 million due to the equivalent amount of CO_2 being reduced using a social cost of carbon of $31/ton$CO_2$ (Nordhaus 2017). Health Benefits, using a Value of Statistical Life of $7.4 million (EPA 2011), across the sectors vary due to differences in location and emission height of the different sectors with all but the Covered Sector (CS) scenario having larger health benefits than carbon benefits. As expected, the health benefits of reducing transportation emissions are the largest given that is the largest emitting sector and the emissions are ground-level rather than elevated. Benefits for CS and Transportation are relatively evenly distributed between disadvantaged and non-disadvantaged communities, but health benefits from reductions in the Refinery and Electricity Generation reductions are concentrated in disadvantaged communities, 69% and 63%, respectively. This demonstrates that while the benefits of carbon emission reductions may be distributed evenly statewide, the benefits of co-pollutant reductions may be distributed unevenly across spatial scale and across sectors.

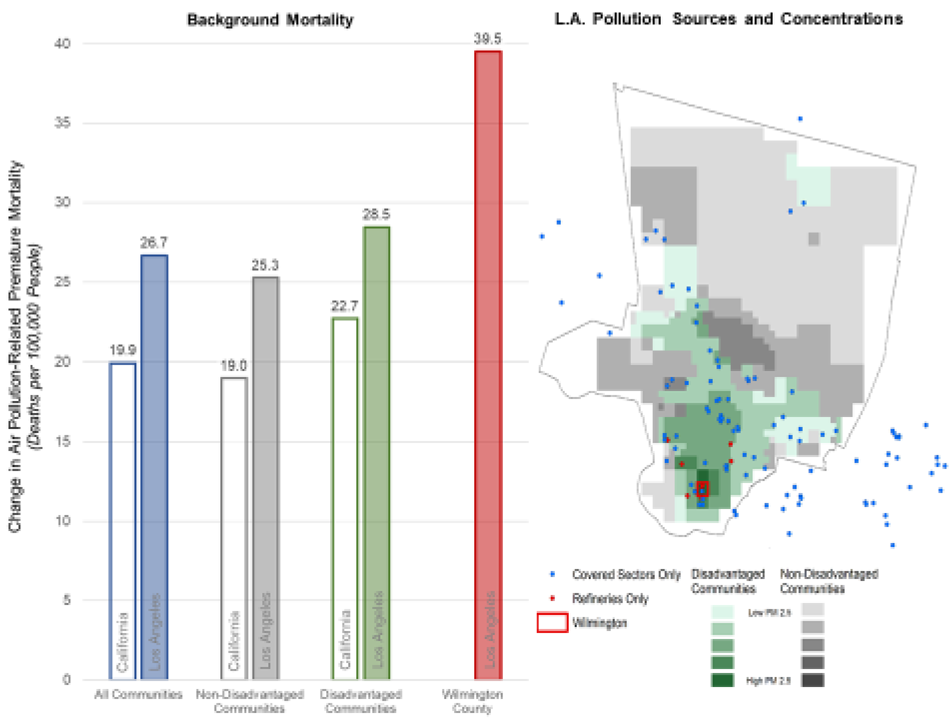
Figure 5-2 Aggregate results under scenarios, comparing climate benefits to health benefits



Previous studies have focused on changes in emission near DA Communities (Cushing et al 2018, Meng 2017) as a proxy for reducing pollution burdens in disadvantaged communities. Others have shown that pollution exposure levels are unequal across the state (UCS 2019). In terms of co-pollutant reductions, Anderson et al. (2018) emphasize an uncertainty in the knowledge of which climate policies will show tangible co-pollutant emission reductions. The results below demonstrate that quantifying this uncertainty is key because each unit of emissions may have different marginal benefits depending on location and sector of the pollution source.

Others have pointed to differentiated levels of exposure within counties, using Los Angeles County as an example, we show the base case premature mortality based on 2014 emissions. We highlight the differences in PM2.5-related mortality as a function of air pollution concentration (micrograms/m3) across the county in Figure 5-2. Communities, such as Wilmington and Southeast LA, show the highest concentrations and premature mortality rates. Mortality caused by ambient air pollution levels is 19.5% higher in disadvantaged communities than non-disadvantaged communities across California. Overall pollution-caused mortality is 33.9% higher in LA County than the state average, but the relative gap between disadvantaged and non-disadvantaged communities is smaller in LA. However, some disadvantaged communities in LA, such as Wilmington, have acute pollution concerns, in part due to proximity to refineries, with air-pollution mortality 98% higher than the state average.

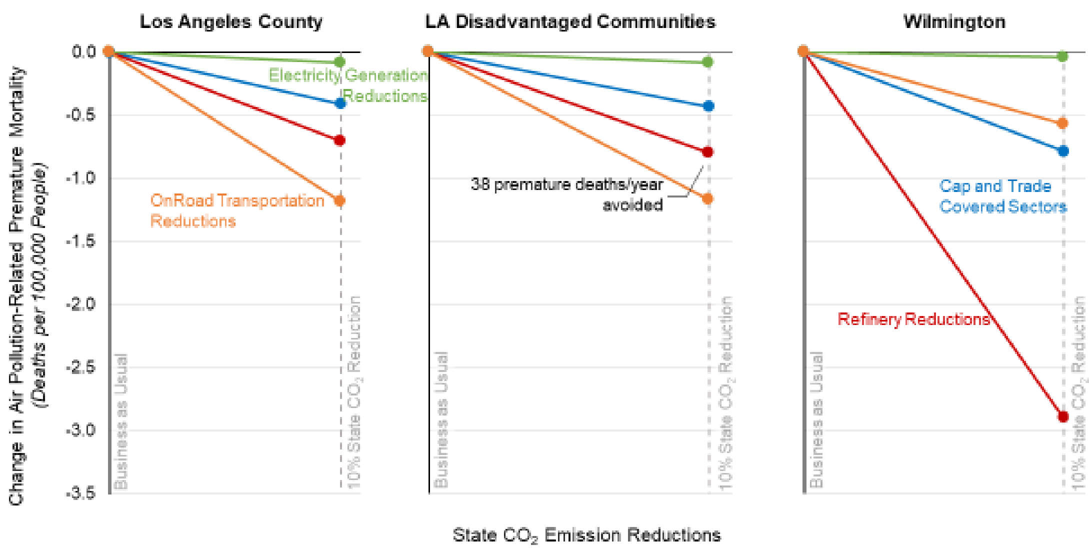
Figure 5-3 Baseline Air Pollution Exposure in LA County, Disadvantaged Communities and Wilmington



3.1 Marginal Benefits across Los Angeles County

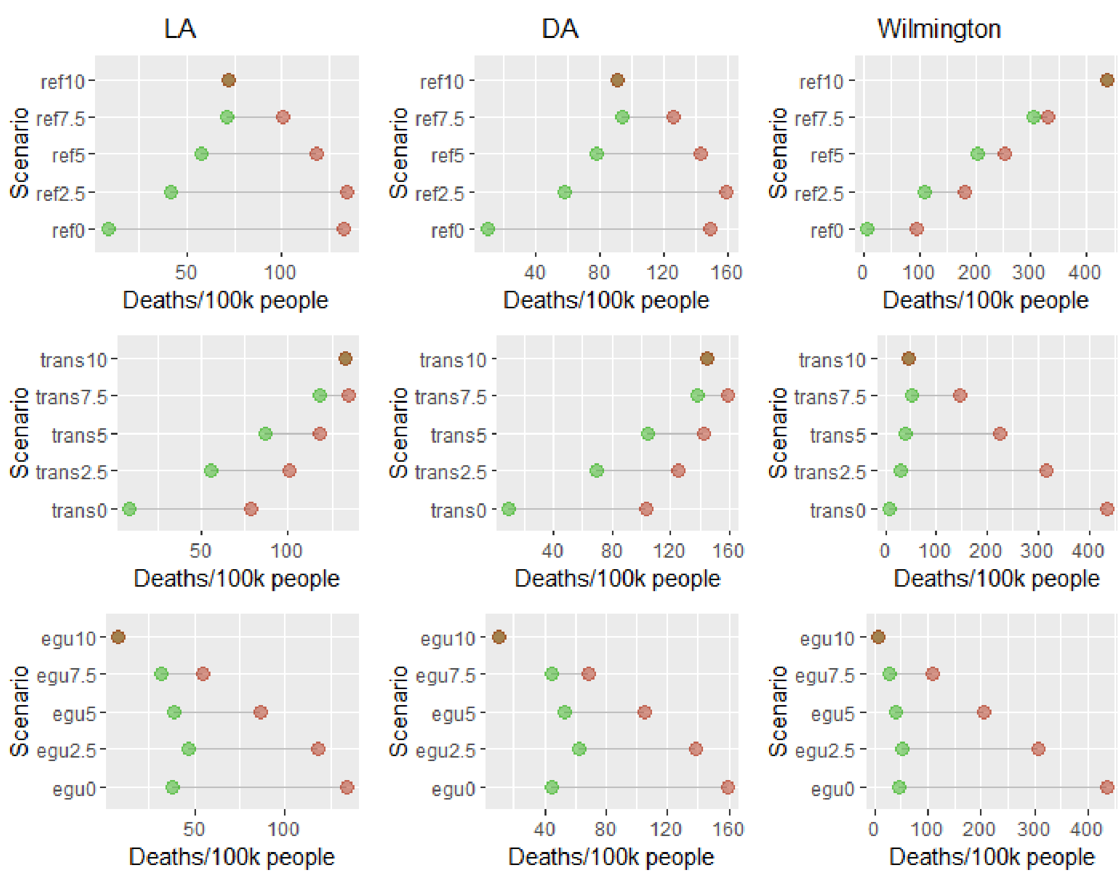
Four scenarios are explored the variation in PM2.5 related health benefits that could occur under the same amount of CO2 emission reductions in Figure 5-4. The three panels separate between marginal benefits in different communities based upon the change in population-weighted PM2.5 exposure in the four scenarios (with green representing electricity generation unit reductions, blue representing covered sector emission reductions, red representing refinery emission reductions, and orange representing onroad transportation reductions). Across all census tracts LA County, the marginal benefits of reducing onroad transportation are the largest with a slope almost 3x that of reducing emissions from electricity generating units only. This relationship appears similar when looking at only the disadvantaged communities in California, where reducing transportation emissions would reduce 64 premature mortalities annually and refinery emission reductions would avoid 38 premature mortalities. When we look at the third panel and focus on the community of Wilmington, the marginal benefits of reducing refinery emissions become the largest, 5x the marginal benefits of onroad transportation. Together these scenarios of equivalent emission reductions indicate that all else equal, different communities will have varied preferences in climate policies due to the differential PM2.5 related health benefits.

Figure 5-4 Normalized Marginal Benefits of 10% Statewide Emission Reductions in LA County



To further explore the differences in marginal benefits across location, we explore 35 combinations of reducing 10% CO2 emissions across the same three spatial boundaries (LA, LA-Disadvantaged Communities, and Wilmington) in Figure 5-5. The first series in all figures represents the same marginal benefits scenario represented in Figure 5-4. The remaining series represent the range of benefits that could occur in the 34 remaining scenarios, where each series represents a common sectoral reduction (e.g 7.5% reduction in refinery, onroad transportation, or electricity generation emissions). The shapes of the marginal benefits curves for LA and LA disadvantaged communities are similar again, emphasizing that onroad transportation will have higher marginal benefits (as the ratio of transportation emissions reductions increase, the amount of premature mortality avoided increases). The range of benefits in the 15 scenarios where refinery or electricity emission reductions are zero is larger due to the range of transportation emission reductions (0-10%) encompassed. The 10% refinery emission reduction is in the middle of this range while the 10% electricity emission reduction is at the bottom of this range, indicating that net benefits in LA will be maximized by policies affecting sectors other than electricity generation. Similar to Figure 5-4, Wilmington prefers refinery emission reductions to maximize benefits, however, it does not appear to have a strong preference for transportation emission reductions over electricity generation emission reductions. The shape of the curves for LA census tracts is similar to that of all CA tracts, with the marginal benefits maximum being greater in LA across all 3 sectors.

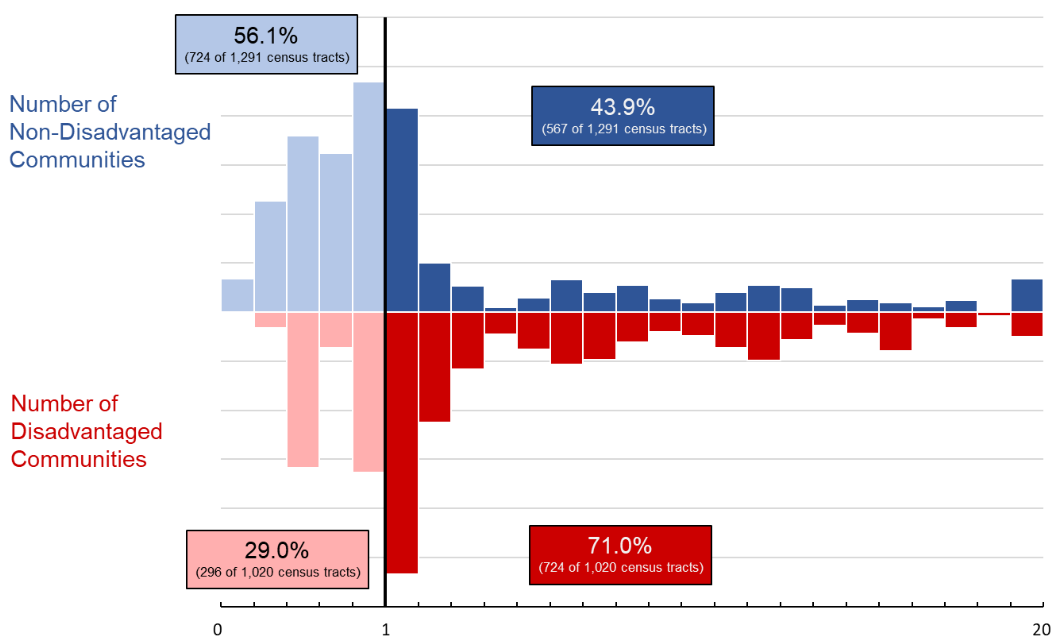
Figure 5-5 Aggregate Benefits (Premature Mortality Avoided) of 10% Statewide Emission Reductions across Refinery, Electricity, Transport Sectors



3.2 Distribution of Benefits across LA Census Tracts

The histograms show the ratio of premature mortality benefits induced by covered sector emissions and refinery only emission reductions in each census tract grouped by the disadvantaged community's designation. Results shown in Figure 5-6 are for scenarios of equivalent levels of 10 MMT CO2 emission reductions spread uniformly among all facilities approximating to 10% covered sector reductions and 31% refinery reductions. As expected, in the majority of non-disadvantaged census tracts covered sector emission reductions have greater benefits, where the ratio is <1. However, the distribution of census tracts which have greater health benefits under a refinery emission reduction scenario is dissimilar when separating between disadvantaged and non-disadvantaged communities. For disadvantaged communities, the majority of communities (>70%) have a ratio greater than one, indicating that in these communities, reductions from refineries will have greater benefits than from covered sectors.

Figure 5-6 Histograms of Refinery and Covered Sector Facility Marginal Benefits Ratio by Census Tract



Note: Horizontal axis represents the ratio of health benefits of an equivalent carbon emission reduction in refineries compared to covered sector facilities in each census tract, with a ratio greater than 1 indicating the benefits of refinery reductions are higher.

4. Discussion and Conclusions

Ideally, flexible climate policies would distribute emissions so that marginal cost of emissions is minimized. However, policymakers are designing market-based and binding GHG emission reductions concurrently, while prioritizing the cost-effectiveness of mitigation. Because climate policies also reduce co-pollutants, which have localized, variable benefits, designing market-based climate policies based on cost alone may not optimize the social benefits of climate policy. For example, the statewide health benefits of reductions in co-pollutants may be higher under command & control, binding climate policies than flexible climate policies, if these binding policies are targeted at disadvantaged communities and urban areas where the marginal benefits of emission reduction are high. This paper takes the first step towards developing tools that would allow policymakers to compare the marginal benefits of the climate policies in California

Much of the debate in the literature has focused on the uncertainty in how much facilities are reducing their emissions based on current climate policies, specifically: 1) how much emissions reduction will be induced by flexible climate policies in aggregate and at the facility-level? 2) whether the distribution of facilities reducing emissions will be distributed equally? Because of the challenges in attributing facility-level emission reductions to a specific policy, our work uses a bounded emissions scenarios approach to look at the range of prospective emissions reductions that could occur at each facility through 2030. In particular, we show that the marginal benefits of sector-based policies in California will likely vary across different spatial scales. Not only are the marginal benefits likely higher in disadvantaged communities due to historical inequities in air pollution exposure, but the range of health benefits that disadvantaged communities could accrue could be highly variable depending on the sector reducing emissions, even if the carbon abatement potential is equivalent. This means that the design and stringency of the suite of flexible climate policies being implemented in California over the next 10 years could have a wide variation of health co-benefits in disadvantaged communities, depending on which climate policies are binding and which serve as backstops.

There's an irresolvable tension in how to condition on multiple contemporaneous policies in California but also in various challenges to power plant regulations such as the USEPA's efforts to further regulate mercury emissions from power plants (Levinson 2018). Current studies are insufficient for robust decision making about which facilities to prioritize given the existence of large co-benefits in aggregate. Future models must be empirically grounded to address these multiple contemporaneous policies, while also measuring benefits at high spatial resolution necessary to determine distribution of benefits among population subgroups.

Here we take the first step using a reduced complexity air pollution model to develop initial estimates of the differential marginal benefits of sector-based climate policies in California. By assessing these benefits at the census tract level, we develop estimates of the how these sectoral marginal benefits are distributed among different spatial scales and communities. This allows us to move beyond the current distance to emitter proxies being used assess the co-pollutant reduction benefits of cap-and-trade and other climate policies in California. Given the lack of information at the facility or industry level on marginal abatement cost curves, we assume a uniform distribution of emission reduction across each sectoral scenario. Future work should estimate differential marginal damages as a function of location, wind speed/direction, and facility characteristics, which would allow us to determine how sensitive the scenarios are to changing locations of emission reductions.

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Appendices

Appendix 1 – Supplemental Information for Chapter 3

1. CFAD Model Description

The CFAD model (Ramaswami et al 2016) estimates fossil fuel energy-related carbon and PM2.5 emissions across 600+ urban areas in China based on the energy use from residential, commercial, and industrial and transportation sectors within each city. The air pollution dispersion model (AERMOD) allows for modeling dynamics of changes in primary PM emissions and the resultant air quality changes based on PM2.5 concentrations. AERMOD (Cimorelli et al. 2005) is a Gaussian plume model that considers the dispersion of primary PM2.5 based on meteorology, topography, and the emission characteristics of primary PM emissions. Location of power plant, cement, and steel plants in addition to downscaled industrial, commercial, and residential energy use allow for a determination of city-wide PM2.5 emissions and changes in annual average PM2.5 concentrations. Premature mortality due to exposure to PM2.5 concentrations is estimated based upon the population for each city, baseline disease incidence rates, and the increase in relative risk due to PM2.5 concentration levels based upon the Global Burden of Disease (Burnett et al 2014; Ramaswami et al 2017).

2. *Scenario Assumptions*

Emission Control Scenarios

PowerPlant/Steel/Cement Controls: This scenario estimates the emissions reduced by installing pollution scrubbers (ESP, FF, etc.) on smokestacks of industrial facilities. For the powerplant, cement, and steel sectors (those sectors for which emissions are available from spatially-specific locations), the impact of increased penetration of various pollution control technologies (Zhao, Zhang, and Nielsen 2014) is estimated based on the National Air Pollution Control Action Plan. The pollution abatement effectiveness of various control technologies (fabric filters, electrostatic precipitators, cyclones, and wet scrubbers) is estimated based on each industry's expected control technology (Lei et al. 2011; Zhao, Zhang, and Nielsen 2013).

Vehicle Fuel Standards: This scenario estimates the emissions reduced from light and heavy-duty vehicle compliance with proposed vehicle fuel standards. Methods to estimate transportation interventions such as proposed fuel standards. Fuel standards for gasoline and diesel vehicles as proposed by the 12th FYP are modeled based on (Shao and Wagner 2015) and using the current 2010 primary energy use (Ramaswami et al 2016) for the transportation sector, estimations of on-road combustion vehicle emission reduction are developed. It is estimated that gasoline vehicles will switch from the China 3 to China 5 standard by 2020 and that heavy-duty diesel vehicles will improve from China 2 to China 3.

PowerPlant Controls: This scenario estimates the effects of power plants control technologies on air quality because Jiangsu already has relatively advanced power generation facilities. A separate scenario was created in order to isolate the individual the effect of in-boundary electricity generation controls compared to industrial point sources. Because Jiangsu is a relatively affluent province, many of the power plants already have significant control technologies, therefore any direct PM2.5 emission impact would be the related to the increased adoption of electrostatic precipitators (ESP) which could decrease emissions by 15% but are more costly (Sun et al. 2014)

Urban Energy Efficiency Scenarios

Urban single sector and cross-sectoral energy efficiency strategies were developed as follows, please see Ramaswami et al. (2017) and Tong et al. (2017) for more detail on the industrial efficiency, building efficiency, and waste heat exchange scenario development

The Industrial Efficiency scenario is modeled as a single-sector approach that would estimate improvements in energy efficiency from powerplants and industrial boilers based on existing policies in the next 10 years. Industrial boiler efficiency is expected to increase by 7.5%(IEA 2010)(IEA 2010)(IEA, 2010), while power plants are expected to become 10% more efficient (IEA 2010).

Building Efficiency is a single-sector approach targeting building envelope and appliance improvements, expected to decrease energy use by 5%-15% due to retrofits in existing building envelopes. This scenario is applied to each city based upon existing residential floor area and costs of policy implementation were determined based upon current subsidies for building envelope improvement (PNNL 2014, IEA 2010)

Waste Heat Exchange is based on an energy cascading algorithm that delineates industrial waste heat by grade (high <400, medium (150-400C), low (<150C) in order to determine the reutilization potential based upon the current industrial reuse of waste heat and the heating demands of potential users in the industrial, residential, and commercial sectors. (see Tong et al. 2017 for further detail on the methodology)

3. *Cost Benefit Assumptions*

Costs

Costs of each policy are measured based upon the changes in emissions each city and the needed investment to implement the policy. Emission control policies take into account the cost of the equipment needed to retrofit industry and power plants, while the vehicle fuel policy takes into account the additional vehicle cost of engine/emission controls to reduce vehicle emissions. Costs for these strategies are scaled by each unit of emissions reduced or each vehicle improved (Amann et al. 2008, Shao and Wagner 2015). Urban efficiency policies consider the cost of implementation based upon the new systems/equipment required by the policy. These strategies are scaled based on the size of the system required for industrial efficiency and waste heat exchange and per unit area for buildings efficiency (Tong et al. 2017, Romankiewicz et al. 2012)

Emission control policies are based on the levelized cost per unit PM2.5 reduced for power plants and industries (Amann et al. 2008) based on expected combustion technologies and their distribution in Jiangsu, China. Total emissions reduced in each sector are estimated based upon the effectiveness of the strategy modeled in the industrial scenarios, while the expected penetration of different pollution control technologies is estimated using (Zhao et al 2014). For the vehicle fuel standard scenario, total emissions reduced in the transportation sector are based upon the fuel standard and the expected number of vehicle turnover with the cost of the policy estimated per vehicle (Shao and Wagner 2015). For urban energy efficiency policies, costs are based on the capital investment needed to implement the three policies. For industry, costs are estimated based projects implemented under the Top 1,000 and Top 10,000 enterprises programs in previous Five-Year Plans and a weighted average of the capital investment required for the case studies is scaled based on the expected energy savings of each project (Romankiewicz et al. 2012). For buildings, costs are estimated at 9.1 RMB/m2 based upon building envelope and insulation improvements that would achieve a 5% energy savings in existing buildings similar to costs estimated in previous studies (PNNL 2011; 2014). For waste heat exchange, costs are estimated assuming construction of new district energy system in each city based upon size of the system required (UNEP 2015) and case studies of Chinese city district heat systems (Tong et al 2017).

Benefits

The benefits of each policy are based upon valuation estimates of the premature mortalities avoided due to the change in city-wide PM2.5 concentration. Benefits from reductions in premature mortality are based on value of statistical life, estimated to be $1 million RMB based on previous studies from 0.6-1.4 million RMB/person (Wang and He 2010, World Bank 2007), assuming the cities in Jiangsu have similar income to Chongqing. Although VSL in developing countries (non-OECD countries) is not well-known due to lack of studies and sensitivity to income variation, our VSL is conservative compared to those used by others (i.e. West et al 2013) where VSL ranged from $1.2-7.4 million USD. The value of carbon emissions is estimated using the Social Cost of Carbon (USEPA 2015). Energy use reduction is valued based upon avoided fuel cost of coal Because the Chinese government set the commodity market for coal prices (Biello 2010) , a low end estimate of 500 RMB/ton coal is assumed. By converting to monetary benefits of carbon mitigation and PM2.5 mitigation, we can evaluate how maximizing the carbon and air pollution benefits of pollution control policies at the city-scale may have different policy tradeoffs and result in different policy preferences than minimizing marginal abatement costs.

4. *Uncertainty*

The authors acknowledge uncertainty in the emissions reduction of each policy, the shape of the PM2.5 exposure-response function, and Value of Statistical Life in non-OECD countries. To verify, the distribution of emission across sectors (industry, buildings, transportation) in each city is compared to other studies of Jiangsu cities (Wang et al 2015). To verify total emissions in each city, emission density (PM2.5/km2) of the 13 cities is compared to a similar study of YRD cities (Wang et al 2014). Debate surrounding the health benefits of PM2.5 reduction in developing countries are acknowledged but we use the globally standardized GBD CRF (Burnett et al 2014, Pope et al 2013) to estimate elevated health risk for adults greater than 30 years of age due to stroke, lung cancer, COPD, and IHD, which account for three of the four leading mortality causes in Jiangsu province. Age distribution and baseline disease incidence rates are specific to the Jiangsu province (IHME 2013). Three of the four diseases included in the GBD CRF are top mortality causes in Jiangsu

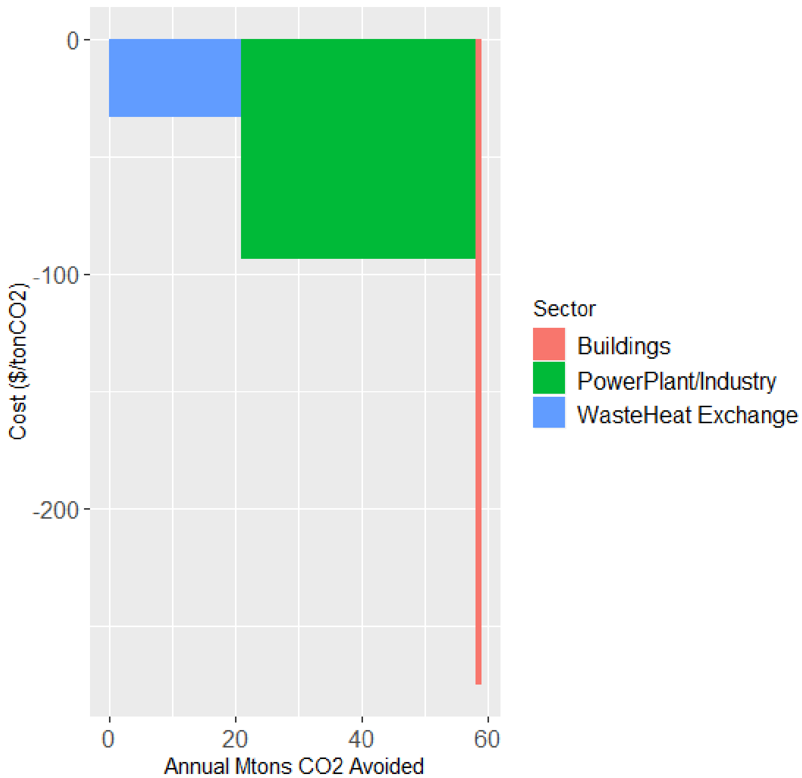
AERMOD Limitations

In our setup of the AERMOD model, we have ignored wet/dry deposition due to limitations in the meteorology data available. Others (Liu et al. 2016) have emphasized the role of regional air pollution transport in meeting air quality targets and concerns have been raised about Shanghai's ability to meet its air quality targets due to its location downwind of significant industrial pollution sources (Lv et al 2015). This study assumes the majority of the urban increment is related with primary PM emissions in urban areas and looking at the change in PM concentration across scenarios should negate the effects of regional transport assuming uniform secondary PM levels. The calculation of health benefits is based on the change in concentration between the base case and the six scenarios, therefore we do not expect this to change the conclusion of the study although we may be underestimating absolute concentrations in the model.

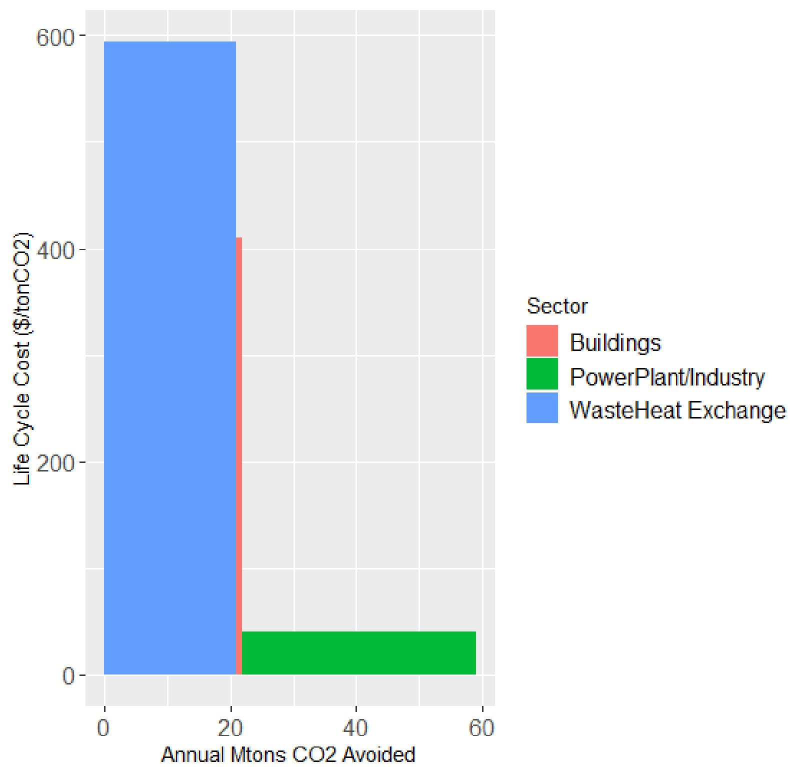
City-wide emission inventory data is limited to one year (temporally) and is based upon the activity occurring in the city's administrative area. Other studies (Wagner et al. 2018, Wang et al. 2014) may estimate emission inventories of urban areas only based upon approximations of built-up area such as nighttime lights or population density. Therefore, in order to compare the city-wide emissions, the emission density (ton/km2) is compared to recent studies of Jiangsu cities (Wang et al 2014)

5. Cost-Benefit Abatement Curves

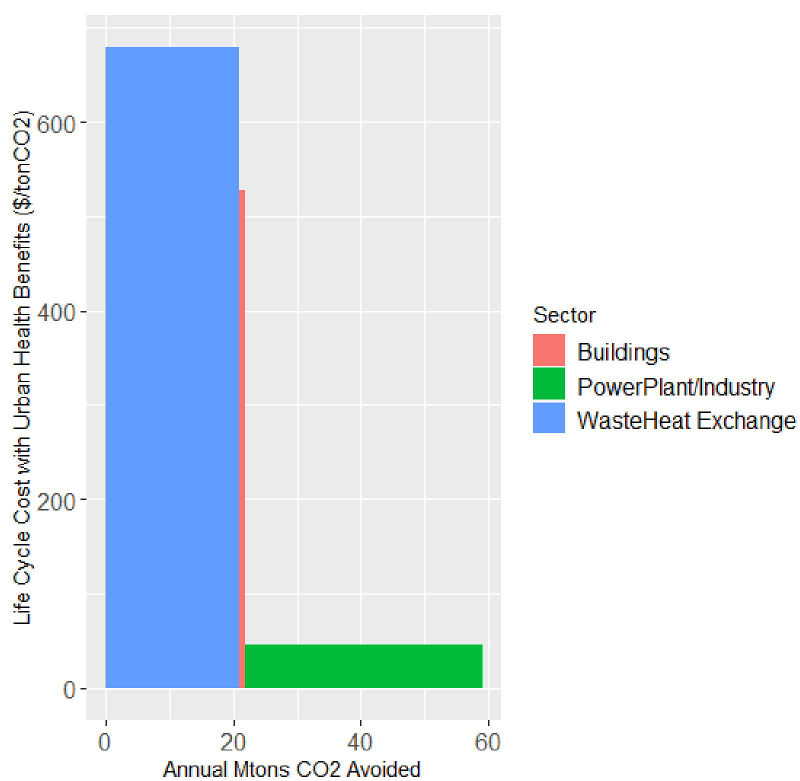
a) Cost ($/ton CO2) vs CO2 Abatement Potential



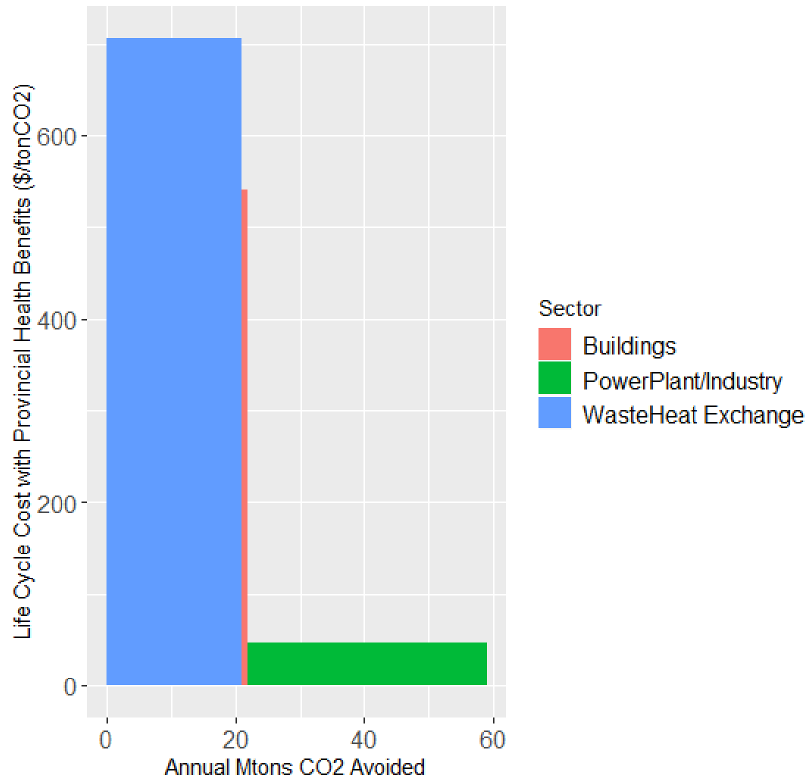
b) Life Cycle Cost ($/ton CO2) vs CO2 Abatement Potential



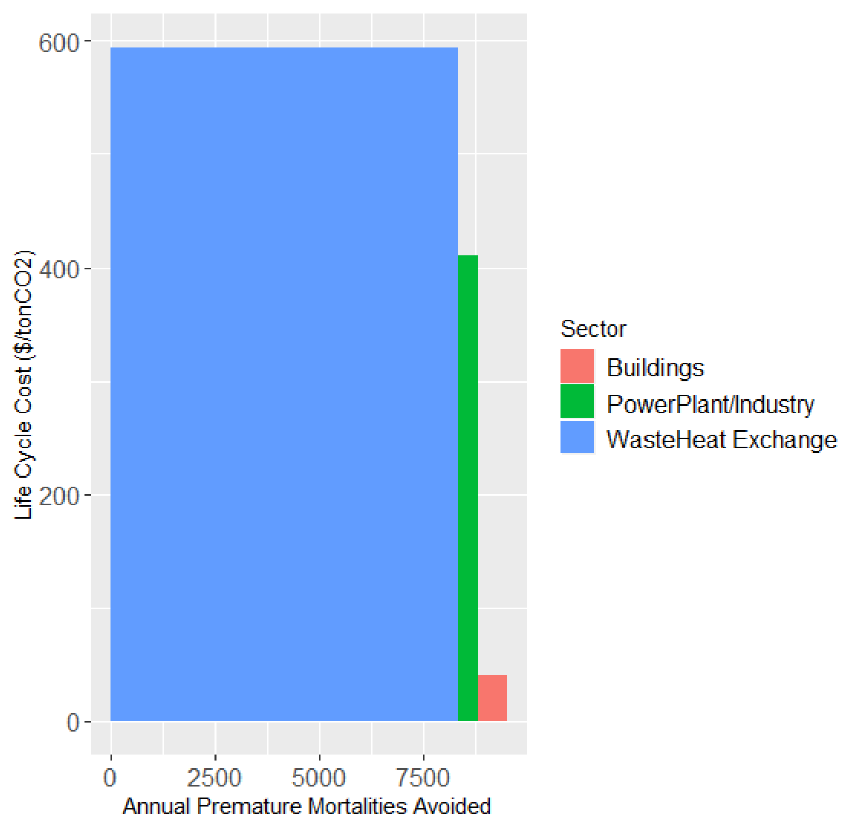
c) Life Cycle Cost + Urban Health Benefits ($/ton CO2) vs CO2 Abatement Potential



d) Life Cycle Cost + Provincial Health Benefits ($/ton CO2) vs CO2 Abatement Potential



e) Life Cycle Cost ($/ton CO2) vs Annual Premature Mortality Avoided



Appendix 2 – Supplemental Information for Chapter 5

Response Account of Environmental Justice Perspectives of California Climate Policies: Providing Political Context for the Modeling Results

Introduction

Although California is seen as an environmental leader nationally, within the state, there are highly concentrated areas of environmental pollution and a healthy advocacy community which seeks to hold polluters accountable while improving the livelihoods of frontline communities.

There are a myriad of concerns regarding the ability of California climate policies to reduce emissions within the state being expressed by environmental groups. The level of offsets and free allocation of permits has stoked fears that local high emission industrial sources will buy credits rather than reduce local emissions. This has created a contentious debate between various academics, NGOs, and the California Air Resources Board over whether industrial facilities near frontline communities are reducing emissions under current climate policy.

The evidence thus far from the public health community is that frontline communities have not seen tangible emissions reductions and that emission may have increased in certain communities (Cushing et al. 2018, Pastor, Morello-Frosch, et al. 2010). Further, due to the uncertainty in which technologies will be used to reduce carbon emissions, others have argued that Cap-and-Trade will not reduce co-pollutants (Anderson et al. 2018) including criteria air pollutants such as PM2.5, SOx, NOx, etc. Others have argued that GHG emissions are being reduced faster in disadvantaged communities (Meng 2017) and that the benefits of cap-and-trade in disadvantaged communities should only be expected from auction revenues (Aufhammer et al 2017). It is currently unclear whether frontline and disadvantaged communities with disproportionate pollution burdens can expect to see any emission reduction benefits from cap-and-trade and the 2017 Scoping Plan Update (CARB 2017)

In order to assuage the concerns of environmental justice groups, a companion bill, AB617 was passed to attempt to monitor pollution levels in highly pollution-burdened communities. AB617 includes mechanisms for a Community Air Protection Program which will improve monitoring network in frontline communities and engage community groups in air quality management planning. Critically, there was no guaranteed funding mechanism for the policy and there is not necessarily an enforcement mechanism beyond the facility permitting process. So while AB 617 improves monitoring in local communities and gives community organizers/residents more influence over air quality management, there is no guarantee that the Community Air Protection Program will improve health outcomes in frontline communities. Environmental justice groups were divided on whether the local benefits of AB 617 were enough to outweigh their concerns about cap and trade.

One of the reasons California has had the political independence to pursue their own environmental policies that are uniquely more stringent is the special waiver California got in the Clean Air Act to enact more stringent regulations due to its decades long struggle with poor air quality. This creates a unique capacity and accountability at the state level for state agencies and air quality management districts (locally) to tailor policies towards alleviating pollution burdens. Nationally, we see this play out in debates over fuel efficiency standards, appliance standards etc. which give California power over national regulators and industry because they can set their own standards. Within the state, this conversation allows a strengthened environmental advocacy community to attempt to hold state agencies accountable and an increasingly nuanced discussion of how environmental policy should address issues of equity.

Although California has made significant progress in improving environmental hazards from air pollution, this progress has not come swiftly enough for many, particularly those in front-line communities which historically have higher pollution burdens and concentrated low income and minority residents. Environmental policies in California, particularly recent climate policy, has been seen as a step forward to many in the climate community, but not sufficient for environmental justice groups advocating for front-line communities. These groups are more concerned with local air pollution and environmental health outcomes and making sure that environmental policy alleviates these burdens, but also interested in climate justice and using cap-and-trade's distributive effects in allocating investments to front-line communities.

Policy Background: Flexible Climate Policies

California state government has put forth significant resources to create flexible climate policy (e.g. cap and trade, renewable portfolio standards, low carbon fuel standard, EV mandates, etc.) that reduces carbon emissions but does not reduce the state's economic competitiveness. The overlapping policies seek to reduce carbon emissions by 40% by 2030 while minimizing the marginal abatement costs of regulated entities (CARB 2017). The cap-and-trade extension (AB398), which extends the current system from 2021-2030, met significant resistance from environmental justice groups who argued that the current cap-and-trade program did not go far enough in reducing pollution burdens in front-line communities.

4. Cap and Trade and 2017 Scoping Plan

California passed the re-adoption of its cap-and-trade program (AB 398) last summer extending a key component of its efforts to reduce GHG emissions by 2030. Emissions regulated by the 2017 Scoping Plan (CARB 2017) are considered "covered sector emissions" and account for roughly 80 percent of all greenhouse gas emissions reported in the state of California. These sectors include point-source pollutants such as large industrial facilities, electricity generation, transportation, and residential and commercial consumers (CARB). Critically, the Scoping Plan does not set any mandatory emissions reduction targets for any particular sector (e.g. oil refineries), although this was considered in the agencies plans prior to the passage of AB 398 (CARB 2017b). Due to the flexibility built into the cap-and-trade market, Renewable Portfolio Standards, Short Live Climate Pollutants, Low Carbon Fuel Standard, and other policies set targets for transitioning away from fossil fuels in the energy (electricity and transportation fuels) sector. Air quality management districts (AQMDs) will continue to regulate regional air quality through programs limiting criteria air pollutant emissions but will no longer have any jurisdiction over GHG emissions reductions. Critics of the current iteration of the cap-and-trade program, generally, point to two specific issues; an oversupply in the allocation of allowances and offsets that will artificially keep carbon prices low removing incentives for covered sectors to invest reducing their emissions.

5. Other Mobile Source Policies

The transportation sector is largest source of carbon emissions in the state and there are various policies in place to reduce vehicle activity and adopt low-carbon fuels. The California Low-Carbon Fuel Standard (LCFS) is anticipated to drive emissions reductions throughout the transportation sector by setting a target on the carbon intensity (g CO2/MJ) of the in-state fuel market. Unlike the statewide cap-and-trade program, the LCFS has not placed a cap on overall sector emissions or set a volume quota on petroleum production, but rather constitutes a primarily supply-side intervention by facilitating a switch in production of alternative, less carbon-intensive fuels (e.g. biofuels, electric, natural gas, hydrogen) in place of conventional gasoline and diesel usage. The LCFS program works concurrently with the Sustainable Communities Strategy which sets targets for reduced vehicle miles traveled (VMTs) at the community level and the ZEV mandate which has set a target of 1 million Zero Emission Vehicles (ZEVs) sold by 2025. These policies together will reduce demand for refined products in California. These changes in in-state demand for gasoline and diesel may induce refineries to invest in efficiency upgrades to reduce costs and emissions, carbon capture and sequestration (CCS) technologies depending on LCFS credit value, or capital investments to export their products. LCFS has faced numerous legal challenges which have led to a steady carbon intensity target since 2015. In the Fall of 2018, the LCFS program was extended to reduce the carbon intensity of transportation fuels by 20% through 2030. The initial program design and the slower than expected ramp up of carbon intensity targets has led to a surplus of credits, mainly generated by biofuel producers. As carbon intensity targets become more stringent, the expectation is that zero emission vehicles powered by electricity, natural gas, or hydrogen will take over the bulk of LCFS credit generation. However, if these new technologies are not adopted quickly enough, then a shortage of LCFS credits may force refineries to either cut production, export refined products, or further reduce emissions.

The interviews in this section attempt to organize the critiques and desires of environmental justice groups in a way that will suggest a path forward for environmental policies that address equity concerns and highlight the gaps in current evidence that could be filled by academics and researchers with the analytical capacity to study overlapping climate and environmental health issues:

Preliminary Findings from Interviews:

1. **Regulatory Distrust**

   Multiple interviewees confirmed regulatory distrust among environmental justice groups who believe that climate policies are not designed to improve the environmental health outcomes in low-income and minority communities. Groups fighting market-based climate policies (e.g. cap-and-trade) both inside and outside California see market-based policies as a giveaway to industries who will buy credits/offsets in order to avoid emission control equipment locally. There are also fears at a local level that industry has too much power over air quality management districts, which is further reinforced by a lack of transparency in the facility permitting process and a lack of data availability about the year-over-year emissions from point source polluters. The Air Resources Board is seen as a backstop to prevent regulatory capture at the permitting level by instituting standardized requirements for Best Available Control Technology and Best Available Retrofit Control Technology (BACT/BARCT) implementation on industrial facilities under Cap and Trade (BAAQMD 2018)

2. Resource Procurement – Reallocation of funding to disadvantaged communities

Interviewees that were not engaged in affecting the design of climate policy instead focused on the mechanisms in place for procuring more funding for local monitoring and infrastructure. One of the key provisions of AB617 is the installation of air pollution monitors in selected communities (CAPP 2018) with high levels of air pollution exposure. This increased coverage of monitoring equipment both verifies that air quality is improving due to reduced emissions from nearby facilities and provides information on the differences in exposure in disadvantaged and non-disadvantaged communities.

Secondly, because of the concerns that cap-and-trade is a regressive policy, the state has dedicated 35% of the cap-and-trade revenue to disadvantaged and low-income communities (GGRF 2018). While it is unclear whether the distribution and amount of funding is sufficient for these communities, there is an established process in place for CARB to work with local governments and NGOs to determine the best use of these funds across a range of potential projects (e.g. affordable housing, increased mobility, zero emission vehicles, energy efficiency, etc.). Therefore, local EJ groups who are skeptical of the local emissions impacts of statewide cap-and-trade and climate policy could instead turn towards these investments as a way to directly reduce local air pollution and improve local livability. In 2018, $250 million was allocated to the Community Air Protection Programs established through AB 617, although it is unclear how much will be allocated moving forward. For local NGOs and EJ groups, this funding mechanism could be critical to meeting multiple objectives, although air quality may not be the prioritized outcome.

3. Public Health Risk and Capacity Deficit

Of the groups interviewed, the public health concerns for frontline communities varied in terms of which pollutants and pollution sources were of the greatest concern ranging from air toxics and fugitive emissions to refinery-specific chemicals like hydrogren fluoride (NPR). Part of this is due to the local context of emission sources, air quality, and relationship with the air quality management district, but a theme throughout the conversations was that there was new data or a lack of data on environmental health contaminants. Without adequate local data on emissions, it is difficult for these groups to determine what the largest risks to frontline communities are. Further, it is difficult to get generalizable survey data of public health outcomes in these communities.

For local groups advocating for these communities, this means that many of the concerns are informed by anecdotes of individual cases of health issues. Further this lack of data means that many of the arguments for these frontline communities devolve into NIMBY-ism, where residents and advocates perceive health risks due to their proximity to industrial facilities. All the interviewees mentioned a lack of local data and the technical capacity to analyze environmental health impacts in frontline communities as an obstacle to influencing permitting and policy decisions

4. **Nested Governance**

   Both air quality management and transportation demand management occur across multiple spatial scales and therefore requires interaction between multiple nested levels of government (e.g. city, county, metropolitan planning organizations, air quality management district, state). There was some concern among the groups that the policies being implemented at these different governance levels are not coherent. While the state agencies can set emission targets and direct funding towards these local and regional governments, effective air quality management and transportation emission reductions will require some coordination between the local government. Given the challenges of reducing emissions from permitted facilities and vehicle pollution thus far, it is unclear whether the mechanisms are in place to enable local governments to meet statewide targets.

5. **Incremental Policy Change vs New Policy**

   The environmental justice groups interviewed did not agree on the preferred pathway for future environmental policy. In particular, there was a question on whether supplemental policies (such as increasing permit prices for facilities nearby frontline communities) could be implemented alongside cap-and-trade or whether there was a need for command-and-control policies to induce direct emission reductions in and around frontline communities. Certain groups acknowledged that too much effort and political capital had been put into cap-and-trade over the past 15 years for there to be a viable alternative in the short-term. Others were openly hostile towards cap-and-trade and had instead turned towards influencing direct action by air quality management districts.

The representatives from the following groups were interviewed to determine how environmental justice groups have been approaching climate policy in California since 2006. These groups advocate for a wide-range of frontline communities across the state and are in engaged in climate or air pollution policies at the state and local level. The range of groups was meant to solicit a diversity of opinion in order to understand how different environmental justice actors are approaching climate policy and how the results from Chapter 4 could be have increased value to these environmental groups.

1. Environmental Justice Advisory Committee
2. Climate Justice Alliance
3. California Environmental Justice Alliance
4. Central California Asthma Collaborative
5. Communities for a Better Environment
6. The Greenlining Institute

Sample Interview Protocol - EJ Groups on Climate and Air Pollution Co-Benefits in California

(0:00)

1. **Introductions**
    a. Overview
    b. Consent

(5:00)

2. **Review Chapter 4 Results**
    a. Describe objectives of study
    b. Review Figures 4-1, 4-3, 4-5
    c. Gather Feedback, Answer any questions

(15:00)

3. **IceBreaker Question**
    a. Who are your constituents
    b. What are the biggest environmental threats to their health

(20:00)

4. **Cap and Trade Attitudes and Goals**
    a. How has your group been involved with Cap and Trade
    b. What changes would you like to see to current policy
        i. Which agencies or organizations do you believe can fix this?
        ii. Who would those changes benefit?

(30:00)

5. **Framing**
    a. What other groups do you work with on environmental justice (or climate justice) issues?
        i. What is the nature of the relationship
        ii. What issues and communities do they focus on?
        iii. Do they frame the connection between environmental justice and climate issues similar to your group? If not, how are they different?

(35:00)

6. **Data**
    a. **Where do you get data and technical capacity from?**
        i. Are there particular NGOs or technical experts that you trust (outside of ARB)?
        ii. What kinds of data or support do they provide?

(40:00)

6. **Closing Remarks**
    a. Are there other groups I should talk with?
    b. Anything that I missed?

Summary

Because California is a leader in enacting environmental policies to limit carbon and air pollution, many of its policies may be being tried for the first time and are imperfect. This requires careful consideration of policy design, particularly when considering multiple objectives of climate, air quality, and equity.

The environmental community and environmental justice groups in California are concerned with improving the equity of pollution burdens and the potentially regressive nature of certain environmental policies. In California, these questions play out in front-line communities with multiple questions regarding whether the existing climate policies will reduce emissions within the state and whether low-income and minority communities will see tangible reductions. EJ groups in California must therefore choose between two positions: 1) Work within the existing policy framework to procure state funding for frontline and influence the direction of future policy implementation 2) Advocate for new environmental policies by questioning the effectiveness and stringency of current policies in place.

Due to the political capital that has already been invested in the passage of current climate policies, it is difficult for state agencies to change directions but they have made efforts to incorporate the concerns of environmental justice groups. State agencies and policymakers have made attempts through California Climate Investments (distributing cap-and-trade auction revenue to disadvantaged communities), Environmental Justice Advisory Committee (gather input from key environmental justice stakeholders), and Community Air Protection Programs (developing air quality management plans with community stakeholders) to make sure that there are attempts to address environmental justice and equity concerns in current environmental policy, but it is not yet clear whether current policies are regressive.

Much of the conversation has focused on keeping the costs of pollution abatement low because state agencies must make the case that regulating carbon is not negatively impacting the economic competitiveness of businesses in California. There is no debate over whether disadvantaged communities have higher pollution burdens currently, but there are questions as to whether in their efforts to minimize cost in environmental policy, state agencies have designed policies that are not maximizing the health benefits of reducing criteria air pollution.

In order to develop environmental policies that are more effective at decreasing pollution in frontline communities, additional evidence is needed in the form of:

1. Transparent data about permitting, emissions, industry expansion/activity to determine how air quality management decisions are being made
    a. Increased air pollution monitor coverage through AB 617 and low cost monitors (e.g. Purple Air) to allow communities track air quality over time
2. Accounting for cumulative pollution impacts (e.g. industrial, transportation, agriculture, other emission sources) in order to determine which sources will have the most impact on local air quality
3. Tools that will account for differential marginal benefits of pollution sources (e.g. one unit of pollution reduced from a refinery and a car have different health impacts)
    - This will allow communities to determine which policies have the most local health benefits and help inform how current policies should be improved moving forward